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Ecological efficiency: The ability to achieve human well-being while limiting environmental impact

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ABSTRACT
To reach the UN’s Sustainable Development Goals, humanity should improve its capacity to achieve well-being and development while reducing its environmental impact. This calls for increased efficiency in the process of transforming natural resources into well-being. We present here a novel indicator called Ecological Efficiency and developed to capture this important aspect of the human-environment relation. We found large differences in efficiency among world countries. We then analyzed the relation between our indicator and several country-level variables encompassing different human dimensions, such as economic, political, and demographic. Results highlighted that demography affects Ecological Efficiency more than other factors.

1. Introduction
The UN’s Sustainable Development Goals (SDGs) are ambitious in trying to simultaneously achieve important human and environmental objectives. The need for relevant indicators able to capture the progress towards each individual goal has been previously expressed (Hak et al., 2016). However, the potential trade-offs between the human and ecological dimensions of sustainability (Goodland, 1995; Henderson and Loreau, 2023; Tamburino and Bravo, 2021) imply that comprehensive indicators able to shed light on the most promising ways to simultaneously improve both dimensions are needed as well.

Even taking into account changes in lifestyle and technology, a certain level of environmental impact is inescapable, since satisfying even the most basic human needs requires natural resources and ecological services (Goodland, 1995; Knight and Rosa, 2011; Smil, 2021). For instance, producing food requires agriculture which, independently of its specific form, uses land subtracted from forests and other natural ecosystems at the expense of wilderness and biodiversity (FAO, 2017; Wilson, 2016). Other basic needs such as housing, hospitals, and schools also require land, materials, and energy, hence exerting an inescapable impact on natural systems. It has been indeed shown that a significant part of the Carbon Footprint of countries, especially wealthy ones, does not derive from private consumption but from public administration spending on transportation infrastructures, health services, defense, education, and other core common-interest activities (Hertwich and Peters, 2009; Ottelin et al., 2018).

Not surprisingly, indicators of human well-being and development, such as the Human Development Index (HDI), tend to exhibit a positive correlation with indicators of environmental impact, such as Carbon Emissions or Ecological Footprint (Bravo, 2014; Moran et al., 2008; O’Neill et al., 2018; Tamburino and Bravo, 2021). Interestingly, this positive correlation is weaker for higher values of human development (Moran et al., 2008; Tamburino and Bravo, 2021), while it is stronger for lower ones. This suggests that in conditions of poverty it is difficult to achieve an improvement in human development and well-being without a parallel increase in the use of natural resources, showing the difficulty to reconcile the two underlying dimensions of SDGs. This also highlights the need for increased efficiency in the process of transforming natural resources into well-being.

In physics, efficiency is a pure number defined as the ratio between the useful energy output and the total energy input in a physical process or system. By extension, efficiency can be defined as the ratio between the useful output produced in a process and the amount of resource input required to produce it. It can have different units depending on the specific output and resources involved in the process. The concept of efficiency captures the two parallel goals of increasing the performance of a process and, simultaneously, reducing the amount of used resources, which is especially important under conditions of resource scarcity and/
or waste reduction pressures. For instance, given the current need to reduce carbon emissions, there is a huge effort today to produce more efficient household appliances and cars able to provide good performances while reducing energy consumption.

Like household appliances and cars, humanity needs to perform well, namely to achieve a high level of human well-being (SDGs 1, 2, 3, 8, 9) while reducing its emissions and consumption of natural resources or, more generally, its environmental impact (SDGs 11, 13, 14, 15). We present here a novel indicator specifically developed to measure this ability and called Ecological Efficiency ($ecoE$). Similarly to the concept of efficiency used in physics, we define it as the ratio between the useful output (human well-being) and the input (environmental impact), both expressed using existing indicators (see Sec. 2).

Previous attempts of integrating together measures of human and ecological performance do exist (O’Neill et al., 2018) and several indicators have been proposed, such as the Environmental Performance Index (Wolf et al., 2022) or the Human Sustainable Development Index (Togtokh, 2011). This integration is typically done by aggregating several sub-components in a comprehensive index. However, to make the various components comparable, the process of aggregation is usually based on rankings rather than measured values and involves the use of arbitrary weights (Wolf et al., 2022; Bravo, 2014). Another proposed indicator is the Environmental Efficiency of Well-Being (EWEB), which explicitly refers to the concept of efficiency (Knight and Rosa, 2011). Nevertheless, the way the authors defined EWEB in practice is very different from the efficiency formula used in physics and and is heavily dependent on the on the arbitrary assumptions made by the authors on the specific form of the regression model between their environmental impact and human well-being indicators. Our proposed indicator, $ecoE$, is instead computed as a simple ratio like in physics, implying that, as long as the indicators used to express human well-being and environmental impact can be considered reliable, $ecoE$ is, by extension, reliable, less arbitrary and easy to compute.

Maximizing ecological efficiency clearly represents a desirable goal for humanity. For this reason, we not only present the details for the construction of $ecoE$ but also perform statistical analyses to investigate the correlation between $ecoE$ and several socio-economic, political and demographic variables at the country level. The main goal of these analyses is to identify the variables that are most likely to promote or hinder the efficiency of countries.

The remainder of the paper is organized as follows: Section 2 presents the construction of $ecoE$, describing in details the indicators selected to express human well-being and environmental impact; Section 3 presents the steps leading to the construction of the dataset and the country-level variables used in the statistical analyses, along with the rationale behind their choice and our hypotheses on their expected effect on $ecoE$; results are finally presented in Section 4 and discussed in Section 5. All details and code used for the dataset construction and model estimations are available as Supporting Information.

2. Ecological efficiency

Efficiency is defined in physics as the ratio between the useful energy output and the total energy input in a system. By extension, it can be seen as the ratio between the useful output produced in a process and the amount of resource input required to produce it. Based on this, we introduce a novel indicator, called Ecological Efficiency ($ecoE$) defined as the ratio between human well-being and environmental impact (here computed at the country level). To avoid the proliferation of ad hoc indicators, we expressed human well-being and environmental impact using existing indicators, selecting them among the ones already proposed and rigorously discussed in the scientific literature. The next sections present the rationale behind the choice of the specific human well-being and environmental impact indicators selected in this work and detail the steps leading to the construction of $ecoE$.

2.1. The human well-being indicator: Healthy Lifetime Income

As an indicator of human well-being, we use the recently proposed Healthy Lifetime Income (HLI), which corrects a country’s per capita Gross Domestic Product (GDP$_{pc}$) — measured in purchasing-power adjusted international dollars (hereafter $ for simplicity) — by multiplying it by the number of years that an average person in the same country can expect to live in good health, a measure known as Healthy Life Expectancy (HALE) (Bloom et al., 2021; Zhang et al., 2023):

$$ HLI = GDP_{pc} \times HALE $$

(1)

Note that, being the GDP$_{pc}$ measured in dollars per capita and year and being HALE measured in years, the resulting unit for HLI is PPP international Dollars per capita. It can be interpreted as the total income that an average person can expect to earn during the years in which she lives in good health. It incorporates both instrumental (income) and intrinsic (health) life goals, making it a simple but informative well-being indicator (Becker et al., 2005; Zhang et al., 2023).

More comprehensive indicators taking into account multiple dimensions of human well-being are possible but usually result from complex aggregations of different sub-components (e.g., Benjamin et al., 2014). Aggregations often rely on ranking rather than measured values (due to the non-comparable units), involve weights and/or ad hoc thresholds (e.g. O’Neill et al., 2018), and hence imply a high degree of arbitrariness. On the other hand, researchers agree that GDP alone is not adequate as a measure of human well-being and proposed several GDP extensions. The most common and widely adopted one is the Human Development Index (HDI) (UNDP, 2022). Nevertheless, the HDI has been criticized because it merges different sub-components — income, life expectancy, and education — arbitrarily weighting them as equivalent and implicitly assuming that they are interchangeable (e.g., with higher GDP compensating for lower life expectancy) (Bloom et al., 2021; Scherbov and Gietel-Basten, 2020). The HLI can instead be computed without having to perform long and complex data collection and integration activities.

Even more relevant for our purposes is that the HDI is bounded by design in the [0, 1] interval, leading to a clustering of many countries around nearly identical HDI values despite fundamental real-world differences in development levels (Zhang et al., 2023). In contrast, the HLI spans over three orders of magnitude: from $4.2 \times 10^4$ $ for Burundi to 8.3 \times 10^6$ for Luxembourg (2019 data) (Zhang et al., 2023). This means that even countries with nearly identical HDI values present much larger variations in their HLI data, a feature that better highlights the real differences among countries.

2.2. The environmental impact indicator: Earth Fullness

As indicator of environmental impact, we used the Earth Fullness, which has been proposed for the first time in Toth and Szigteti (2016) and then used in Tamburino and Bravo (2021) to define the Ecological Balance of countries. Earth Fullness is based on one of the most widely adopted indicators of environmental impact: the Ecological Footprint (EF), which represents an estimate of people’s consumption of ecological capital (Kötzes et al., 2009; Wackernagel and Rees, 1996; Wackernagel et al., 1999).

The EF is a consumption-based indicator and hence has the advantage of internalizing the potential displacement of environmental impact, occurring both within (Liu et al., 2022) and across national borders (Grazi et al., 2007; Peters et al., 2011), when wealthier areas or countries become less dependent from local ecosystem services by importing natural capital through trade (Andersson and Lindroth, 2001). The EF attributes the environmental impact to consumers, avoiding the risk of misinterpreting as sustainable a high quality of the local environment achieved at the expense of the global one (Bagliani et al., 2008).

A further advantage of the EF is that it is expressed in global hectares,
namely units of surface with world average bio-productivity. This is the same unit used for Biocapacity (BC), which refers to the capacity of a given area of land or sea to (re)generate resources (Global Footprint Network, 2023a). Having the same unit, EF and BC can directly be compared, which provides a simple criterion for environmental sustainability: the total EF of a country (or any other geographical area) needs to be smaller or equal to its BC. In formula:

$$BC \geq EF$$

(2)

It is worth noting that respecting the criterion above is a necessary condition for being sustainable but, according to many scholars, it cannot be considered sufficient because the ecological footprint is mainly based on the carbon balance (Giampietro and Saltelli, 2014; Blomqvist et al., 2013). While carbon balance is fundamental, environmental sustainability also involves other aspects, such as limiting biodiversity losses or water consumption, which are not captured by the ecological footprint analysis. Even considering these caveats, a recent review recognizes significant merits to EF for both scientific research and policy making, especially when used in conjunction with other indicators (Zhang et al., 2017).

The criterion in (2) leads to concept of Ecological Deficit/Reserve (often simply called Ecological Deficit) of a country, namely the difference $BC - EF$. Since this measure is strongly dependent on the country size, in order to allow inter-country comparability, the per capita Ecological Deficit is usually computed. However, this is also problematic since countries with extremely large total Ecological Deficits may actually have small per capita deficits just because they are densely populated. For instance, India has a per capita Ecological Deficit of only 0.7 gha/cap., but its total EF is more than three times larger than its BC, while the United States have a per capita Ecological Deficit of 4.1 gha/cap, but their total EF is only twice their BC (Global Footprint Network, 2023b). This example shows that the per capita Ecological Deficit does not properly reflect the pressure exerted on the local natural systems (also see Tamburino and Bravo, 2021).

Earth Fullness (hereafter $F$) overcomes such a limit because it is given by the ratio between total ecological footprint and total Biocapacity of a given country:

$$F = \frac{EF}{BC}$$

(3)

This better captures the ecological burden of a country and, simultaneously, keeps inter-country comparability. Moreover, Earth Fullness also provides immediate information about the ecological sustainability of a country, as can be easily derived from (2); $F \leq 1$ is equivalent to having an ecological reserve, while $F > 1$ is equivalent to having an ecological deficit. More in general, the higher the Earth Fullness, the more unsustainable the country and vice-versa.

As given by the ratio of two indicators with the same unit (gha), the Earth Fullness is a positive pure number and spans across five orders of magnitude from 0.04 for Suriname to 104.61 for Singapore.

### 2.3. Definition of the ecological efficiency indicator

We define the Ecological Efficiency ($ecoE$) as the ratio of the two indicators presented in Equations (1) and (3):

$$ecoE = \frac{HLI}{F} = \frac{GDP_{pp} \times HALE \times BC}{EF}$$

(4)

The unit of $ecoE$ is $ per capita, since it is a given by the ratio between HLI, which is in dollars per capita (see Section 2.1), and $F$, which is a pure number (Section 2.2). The Earth Fullness $F$ acts as a correction factor, reducing $HLI$ when a country is not sustainable, namely when $F > 1$, and vice-versa increasing it when $F \leq 1$ (see the sustainability criterion in 2). Clearly, $ecoE$ is always positive and approaches infinity only when $EF \to 0$. In practice, this never happens as long as there are humans in a country, because human activities always imply an impact on the environment (Goodland, 1995; Knight and Rosa, 2011; Smil, 2021).

It is worth noting that a high $ecoE$ does not automatically imply that the environmental impact of a country is low, just like a high efficiency for a household appliance does not imply low energy consumption in absolute terms, but only relatively to its level of performance. Likewise, a high $ecoE$ means that the environmental impact of a country is only relatively low, namely low for the level of well-being achieved in that country. In other words, $ecoE$ provides information on how effectively a country uses the available biocapacity: a country with a high $ecoE$ uses biocapacity optimally, while a country with low $ecoE$ depletes biocapacity without producing welfare for its citizens. By becoming more efficient, the country could improve welfare without increasing impact. Considering the current deficit in biocapacity, maximizing $ecoE$ is clearly a desirable outcome.

### 3. Methods

#### 3.1. Dataset construction

This section briefly presents the sources of data used in the analysis. More detailed information along with the code used to build the dataset are enclosed as Supporting Information. Data used to build $ecoE$ following Equation (4) include:

- **HLI data** for 2010, 2015, and 2019, extracted from the Zhang et al. (2023) article. HLI data older than 2010 had too many missing observations and are not included in the analysis.
- **Earth Fullness** data covering the 2010–2018 period, computed starting from EF and BC estimations extracted from the Global Footprint Network database using the dedicated API (Global Footprint Network, 2023b).

All data used to study the relation between $ecoE$ and socio-economic variables were extracted from the World Bank and V-Dem databases. Section 3.2 shows descriptions for all selected variables and the rationale for their choice.

To harmonize the different variables, often measured in slightly different years for different indicators and countries, we selected three time intervals centered around the available HLI data. These time intervals cover, respectively, the 2009–2011 (hereafter referred as $t_0$), 2014–2016 ($t_1$) and 2018–2020 ($t_2$) periods. For each time interval, indicator, and country, we select the most recent available data.

#### 3.2. Relation between $ecoE$ and socio-economic variables

Being interested in understanding how to promote a high ecological efficiency, we chose a set of country-level variables and performed statistical analyses to see their relation with $ecoE$. We chose variables that, according to the literature, influence human development and environmental quality and we divided them into three groups: economic, political and demographic variables (Table 1). The selected variables are presented below, along with the rationale behind their choice and our hypotheses on their expected effect on $ecoE$. More details on all variables and data sources are available as Supporting Information. Note that our choice is not exhaustive and further variables can be analyzed in future studies.

| Country-level covariates selected for the analysis. |
|-----------------|-----------------|-----------------|
| Economic        | Political       | Demographic     |
| Gini index      | Democracy index | Population density |
| Service proportion | Fertility rate | Population over 65 |
| Education expenditure |                |                  |

Table 1
3.2.1. Economic variables

The most commonly studied economic variable is the country GDP, which is included in the HLI definition (Equation (1)). This means that, if added as independent variable in our models, it would introduce a correlation by design and hence represents a “bad control”, potentially altering the true effects of other regressors (Cinelli et al., 2022). We recognize that its exclusion from the pool of explanatory variables may represent a limitation of ecoE and further discuss this issue in Section 5. The explanatory variables that we instead included in the analysis are: an indicator of income inequality, the Gini index (pure number); an indicator of the country’s economic structure, namely the added value of the service sector as proportion of the country GDP (pure number); and the government expenditure on education as proportion of the country GDP (pure number).

Recent studies suggest that income inequality is a major driver of environmental impact (Chancel, 2022; Nielsen et al., 2021), which implies that a higher Gini index should be negatively associated with ecoE. A higher added value of the service sector is associated with a more mature and less resource-intensive economy and is hence hypothesized to be positively associated with ecoE (V-Dem, 2023), which is hypothesized to be positively associated with productivity. Finally, education expenditure is higher in future-oriented efficient economies, is usually linked to technological development, and is hence hypothesized to be positively associated with ecoE (Balaguier and Cantavella, 2018; Shafiullah et al., 2021).

3.2.2. Political variables

Political variables analyzed here are limited to the Electoral Democracy Index (pure number), estimated as part of the V-Dem, project (V-Dem, 2023), which is hypothesized to be positively associated with ecoE on the basis of previous research (Povitkina and Jagers, 2022; Dinga, 2023).

Some of Hofstede’s cultural dimensions, and notably the Long-Term Orientation index (Hofstede et al., 2010), where initially hypothesized to be also associated with ecoE as well. However, this indicator presents a large number of missing observation and is only available for 10. We hence decided not to include it in subsequent analyses.

3.2.3. Demographic variables

Demographic variables include population density (measured as people/km²), fertility rates (children per woman), and proportion of elderly people (i.e., 65 and above) over the total population (pure number). Population density and high fertility rates reduce the available BC per capita and tend to increase environmental impact (Apergis and Ozturk, 2015; Potts, 2007; Tamburino and Bravo, 2021). They are hence hypothesized to be negatively associated with ecoE.

The effect of an aging human population on sustainability is complex, mediated by several mechanisms through its effects on innovation, consumption, and economic growth, and is widely debated in the literature (Götmark et al., 2018; Jarzebski et al., 2021; Kluge et al., 2014; Liddle and Lung, 2010; Yu et al., 2023). For this reason, we decided to include this variable in our models without advancing any specific hypothesis on the direction of the tested association.

4. Results

4.1. Distribution and ranking

By applying Equation (4), we estimated ecoE for 171 countries with adequate data at time t2 (171 at times t1 and 168 at time t0). The resulting values for the ecoE fall within a range broadly comparable to the HLI one. Nevertheless, since F acts as a correction factor (see Section 2.3), the ecoE range is somewhat larger, spanning from 10² $ to 10⁷ $, with its upper limit that is one order of magnitude higher than the HLI one (see Sec. 2.1).

The resulting ecoE distribution is strongly right-skewed. This holds for all three time intervals, with only limited differences among them (Fig. 1 left). We will hence use for both visualizations and analyses the natural logarithm of the variable, which has the nice property to reduce the variance while keeping the ranking unchanged. This leads to a variable with better statistical properties and easier to visualize without altering the country ranking (Fig. 1 right).

Fig. 2 shows a map with ecoE values for all world countries at t2 (A) and changes between t0 and t2 (B). High-ecoE countries often are developed ones with low population densities located in both the Northern and the Southern hemisphere. Low-ecoE countries tend to be poorer and cluster in Africa and Southern Asia. Conversely, countries showing the highest improvements over time tend to be middle-income ones in Central-East Asia, with individual countries showing significant progress also in Africa, Eastern Europe, and Southern America.

Table 2 shows the top 12 and bottom 12 countries ranked on the base of their ecoE. Interestingly, the top 12 is a mix of wealthy countries, such as Canada, New Zealand and Scandinavian countries, and countries with a somewhat lower income but good ecological balance (or, equivalently, low Earth Fullness, Sec. 2.2), such as Gabon, Guyana and Suriname coming first in this ranking. Other wealthy countries — such as Arabian Gulf countries, the US and, European countries outside Scandinavia — do not appear in the top 12 because of their low ecological balance high (or, equivalently, their high Earth Fullness), which significantly reduces their HLI.

The bottom 12 countries in the ecoE rankings show a strong overlap with the world’s poorest countries. Nevertheless, some poor countries with a relatively good ecological balance (e.g., Mozambique, Madagascar, Sierra Leone and Democratic Republic of Congo) do not appear among the bottom 12. Instead, the list includes some middle-income countries characterized by a large negative ecological balance, such as Comoros, Lesotho, and Zimbabwe, belonging to the lower-

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**Fig. 1.** Density distribution for ecoE (left) and ln(ecoe) (right) in each of the analyzed time intervals.
It is interesting to analyze the relation between ecoE and other indicators covering partially overlapping dimensions, such as the Environmental Performance Index (EPI) and the Human Sustainable Development Index (HSDI). The EPI is a composite index grouping 40 performance indicators in three “policy objectives”, respectively estimating the vitality of ecosystems (Ecosystem Vitality), the effect of environmental conditions on health (Environmental Health), and the progress towards climate change mitigation (Climate Change) (Wolf et al., 2022). The three objectives are then aggregated in one final performance index ranking 180 world countries. The correlation between ecoE and EPI is positive but modest: \( r = 0.50 \) with the overall EPI index, \( r = 0.56 \) with environmental health, \( r = 0.43 \) with ecosystem vitality, and \( r = 0.30 \) with climate change.

The HSDI is an attempt to amend UN’s Human Development Index (HDI) by incorporating an environmental dimension, namely CO₂ emissions (Togtokh, 2011; Bravo, 2014, 2018). Unlike the HDI case, HSDI measures are not regularly estimated by any official institution and 2019 data were hence computed for the purpose of this paper (see Supporting Information). The correlation between ecoE and HSDI is somewhat higher than the one with EPI but still far from perfect (\( r = 0.59 \)).

More generally, despite some limited overlapping with existing indicators, the ecoE seems to bring significantly new (or at least different) information and has the further advantage of being easy to compute starting from HLI and Ecological Footprint data.

4.3. Relation between ecoE and socio-economic variables

We performed statistical analyses to explore the relation between ecoE and country-level socio-economic variables in order to identify the ones that likely promote a high ecological efficiency. As explained in Section 3.2, the selected variables are divided into three groups: economic, demographic, and political.

Notably, certain variables displayed moderate levels of correlation with ecoE, particularly when we examined its logarithmic transformation, as explained in Section 4.1. Specifically, we observed a correlation coefficient of 0.51 for population over 65, \(-0.48\) for fertility rate, and 0.46 for the level of democracy. For most other variables, the correlation coefficients were lower, typically around 0.2 or even less (see Supporting Information). However, some of these relations could be spurious, as suggested by the correlation matrix presented as Supporting Information. Multivariate analysis, including partial-R² statistics, is presented below.

We first estimated three separate multiple regression models (one for each group) where all variables in the group are used to predict ecoE (Models 1–3 in Table 3). Note that the omitted covariates in these models — and especially in Model (2) only including the democracy index as regressor — most likely inflate the amount of the ecoE variance they explain. To get a more comprehensive and reliable picture, we hence estimated two further models, one simultaneously including all variables (Model 4) and one including all variables except the Gini index (Model 5). The reason for dropping the Gini index in the last model was the large number of missing observations in this variable. In order to avoid estimation biases due to the large heteroscedasticity of the data, the natural logarithm of ecoE was used as dependent variable for all models.

Table 3 shows OLS estimates of all models using \( t_2 \) data. We also estimated mixed-effect models taking into account all three time intervals and including a random intercept for countries. Since result were similar, although the large number of missing observations affected the significance of some coefficients, we only report OLS results here, while the mixed-effect estimations are presented as Supporting Information.

The Gini index is neither significant in Model (1), only including economic variables, nor in the full model including all variables (4), middle income country group, and Jordan and Iraq, belonging to the upper-middle income country group, according to the World Bank definition. The list also includes a high-income country, namely the Barbados islands.
hence not supporting the hypothesis of an increased ecoE for more unequal countries. Note that this variable presents many missing observations. We hence estimated a further model (5) including all variables but the Gini index.

Consistently with our hypothesis, the service proportion is positive and significant in Model (1). However, it loses significance when included together with non-economic variables in Model (4) and even turns negative in Model (5), showing an overall modest and uncertain effect on ecoE.

Education expenditure is positive and significant in Model (1) but loses of significance when included when other variables. Although its effect looks broadly consistent with our hypothesis, it is probably smaller in comparison with other variables.

In line with our expectations, the Democracy index is positive and significant in Model (1) but shows the standardized coefficients relative to Model (4) along with their confidence intervals. The (negative) effect of population density is weakly significant ($p < 0.1$) in the full models (4, 5), perhaps because of some collinearity with both economic variables and the Democracy index.

Given the weight of demographic variables emerging from the regressions, it is interesting to analyze the variation in (the logarithms of) ecoE. At the extremes of the population variation range, two opposite dynamics are instead visible. The left-hand side of the Figure includes a group of countries, mainly Eastern European ones, with decreasing population and increasing Ecological Efficiency. The right-hand side of the Figure instead includes countries, mainly Middle East and African ones, showing a strong population increase and increasing Ecological Efficiency. The middle or high-income ones with low population densities and high Biocapacity per capita. It is worth noting that all continents but Asia are represented in the top-12 countries. In the relatively short period under consideration, the largest improvements in ecoE were recorded in Easter Asia and Europe, with the exception of the Middle East, although exceptions to these trends do exist e.g., Uruguay that vastly increased its ecoE without reducing its population, Greece that slightly declined in both population and Ecological Efficiency, or Ethiopia that managed to increase its ecoE despite a rapidly rising population — this analysis is consistent with the idea of a negative impact of demographic growth on ecological efficiency.

To highlight the relative effects of the different variables, Fig. 3 shows the standardized coefficients relative to Model (4) along with their confidence intervals. The (negative) effect of population density is approximately twice the one of fertility. All other variables have much smaller or no effects, with only the Democracy index and the proportion of population over 65 reaching or approaching statistical significance (the latter being only significant at the 10% level).

In addition, we computed the partial $R^2$ statistics by groups of variables (Cinelli and Hazlett, 2019) for the models (4) and (5) in Table 3. In model (4), demographic variables together explain 50% of the total variance of ecoE, economic variables 3%, and democracy 6%. In model (5), demographic variables explain 25% of the ecoE variance, economic variables 3%, and democracy 5% (see Supporting Information).

### Table 3

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<th>(3)</th>
<th>(4)</th>
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</tbody>
</table>

To highlight the relative effects of the different variables, Fig. 3 shows the standardized coefficients relative to Model (4) along with their confidence intervals. The (negative) effect of population density is approximately twice the one of fertility. All other variables have much smaller or no effects, with only the Democracy index and the proportion of population over 65 reaching or approaching statistical significance (the latter being only significant at the 10% level).

In addition, we computed the partial $R^2$ statistics by groups of variables (Cinelli and Hazlett, 2019) for the models (4) and (5) in Table 3. In model (4), demographic variables together explain 50% of the total variance of ecoE, economic variables 3%, and democracy 6%. In model (5), demographic variables explain 25% of the ecoE variance, economic variables 3%, and democracy 5% (see Supporting Information).

Given the weight of demographic variables emerging from the regressions, it is interesting to analyze the variation in (the logarithms of) ecoE. At the extremes of the population variation range, two opposite dynamics are instead visible. The left-hand side of the Figure includes a group of countries, mainly Eastern European ones, with decreasing population and increasing Ecological Efficiency. The right-hand side of the Figure instead includes countries, mainly Middle East and African ones, showing a strong population increase and increasing Ecological Efficiency. The middle or high-income ones with low population densities and high Biocapacity per capita. It is worth noting that all continents but Asia are represented in the top-12 countries. In the relatively short period under consideration, the largest improvements in ecoE were recorded in Easter Asia and Europe, with the exception of the Middle East, although exceptions to these trends do exist — e.g., Uruguay that vastly increased its ecoE without reducing its population, Greece that slightly declined in both population and Ecological Efficiency, or Ethiopia that managed to increase its ecoE despite a rapidly rising population — this analysis is consistent with the idea of a negative impact of demographic growth on ecological efficiency.

5. Discussion

The definition of the Ecological Efficiency indicator allowed us to highlight significant differences among world countries on how environmental impact translates into human well-being, as well as interesting dynamics over time. Most high-efficiency countries are upper-middle or high-income ones with low population densities and high Biocapacity per capita. It is worth noting that all continents but Asia are represented in the top-12 countries. In the relatively short period under consideration, the largest improvements in ecoE were recorded in Easter Asia and Europe, with the exception of the Middle East, although exceptions to these trends do exist — e.g., Uruguay that vastly increased its ecoE without reducing its population, Greece that slightly declined in both population and Ecological Efficiency, or Ethiopia that managed to increase its ecoE despite a rapidly rising population — this analysis is consistent with the idea of a negative impact of demographic growth on ecological efficiency.

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individual countries in other continents also show very positive trends (e.g., Uruguay). A reduction of Ecological Efficiency was instead recorded in several Middle East and Gulf countries, as well as in individual countries in Africa and Southern America. The lowest ecoE levels are mainly observed among poor countries in Africa and some countries in southwestern Asia, such as Iraq and Afghanistan. Theoretically, those countries have a large margin for improvements: simply by becoming more efficient, they could improve their welfare without increasing their environmental impact and/or reduce their impact without affecting their welfare. As emerged from our analysis, becoming more efficient might not be easy in practice and could be hindered by several factors.

The investigated factors include economic, political and demographic variables. GDP is not explicitly included but is implicitly captured since it is part of the ecoE definition. This reflects in the ecoE rankings, where high-income countries tend to be at the top, with some notable exceptions, while poorer ones lies often at the bottom.

Among other economic variables, the most surprising result is that the Gini index shows no significant association with ecoE in any of the estimated models. The idea that a more even distribution of wealth leads to more efficiency makes intuitively sense and is in line with the wide-spread assumption that inequality is a major driver of environmental impact (Cushing et al., 2015; Nielsen et al., 2021). Nevertheless, unequal countries do not score worse in our analysis. This could partially derive from the large number of missing observations in the Gini index variable. Other economic factors such as the service share of the economy or the share of expenditures in education show limited, if any, effects on ecoE as well. Even if these variables are often debated in the literature (e.g., Chu, 2020; Shafiullah et al., 2021), they seem to only play a minor role in our analysis.

The hypothesis that democracy is positively related to Ecological Efficiency is instead supported. Although this factor only has a limited effect (Fig. 3), the related coefficient is significant in all models, confirming the idea that social-liberal democracies tend to adopt more effective environmental policies (Povitkina and Jagers, 2022; Dinga, 2023).

The group of variables showing the strongest effect on Ecological Efficiency is the demographic one (see Section 3.2.3). Population density is the variable having the strongest effect on ecoE among the ones examined here (Fig. 3). This is consistent with previous analyses finding a link between population density and environmental pressure (Apergis and Ozturk, 2015; Potts, 2007; Tamburino and Bravo, 2021), but it is still surprising that this effect lasts even when considering efficiency, i.e., the ability to transform natural resources into well-being.

Fertility rates are logically related to population density (at the net of in/out-migration flows), even if their effects only become visible in the longer term. In the shorter term, they has been instead hypothesized that high fertility rates may displace public and private investments from long-term goals (including ecological efficiency) to more urgent needs (e.g., building schools and other infrastructures) (Asongu, 2013). This may explain the negative effect of fertility rates on ecoE. In addition, Fig. 4 shows that countries experiencing rapid population growth have difficulties in achieving high Ecological Efficiency, and may even reduce it over time, which further confirms the investment-displacement hypothesis. This result is also consistent with the last IPCC report and recent research showing that demographic growth can hinder a reduction in greenhouse-gas emissions (IPCC, 2022; Tamburino et al., 2023).

Less clear is the effect of the share of older people (≥ 65 years) on efficiency. The environmental effect of aging populations is often debated in the literature (Jarzebski et al., 2021). Some scholars argue that older people consume less than younger ones (Kluge et al., 2014; Wei et al., 2018; Zagheni, 2011), others that they consume more due to higher car use, home heating, and medical care (Long et al., 2019; Nansai et al., 2020). Another common view is that aging societies are less innovative, risking hence missing the potential carbon-reducing effect of technological advances and human capital accumulation, which was partially confirmed by a recent study (Yu et al., 2023). Nevertheless, the same study shows that such an effect is weak and other factors prevail in determining carbon emissions. The effect of the over-65 proportion on ecoE is also weak according to our analysis, but positive (Fig. 3). It is significant at the 95% level in model (1) only including demographic variables, and at the 90% level in the full models (4 & 5, Table 3). Our analysis hence does not support the hypothesis of the missed carbon-reducing effect in aging societies and seems more consistent with arguments considering aging as broadly positive for the environment (Götmark et al., 2018; Kluge et al., 2014).

Since our indicator is based on the concept of efficiency, which is well established in physics and engineering and easy to understand, its main limits depend on the reliability of its components, namely the indicators of human well-being and environmental impact. For the former, we selected the HLI, which is relatively new but, as explained in Section 2.1, presents several advantages in comparison with more common indicators such as the Human Development Index (Zhang et al., 2017, 2023). It is also worth noting that the ecoE formulation (Equation (4)) easily allows the replacement of HLI with different indicators without changing the conceptual meaning of ecological efficiency. For instance, HLI could be replaced by a more comprehensive indicator taking into account, for example, the Human Development Index (HDI) or the Gross Domestic Product (GDP) per capita.
account broader dimensions of human well-being (O’Neill et al., 2018).

Replacing HLI with a different indicator of well-being not including GDP could instead allow researchers to include GDP in the pool of explanatory socio-economic variables affecting ecoE. This could represent a solution to the “correlation by design” problem discussed in Section 3.2.1. However, since GDP is an important component of most current well-being indicators (e.g., HDI), doing this may require significant additional research to decouple well-being from income-related measures (Fanning and O’Neill, 2019), which is something beyond the scope of this paper.

Regarding the indicator of environmental impact, the choice of F might seem questionable since this indicator, as well as its equivalent Ecological Balance, is not widely adopted yet (Toth and Szijeti, 2016; Tamburino and Bravo, 2021). However, F is derived from the well consolidated concept of Ecological Deficit (Ritzes et al., 2009; Wackernagel et al., 2015) and improves it by allowing higher comparability between countries of different sizes without the downsides linked to the use of per capita values (see Section 2.2). This makes it a solid indicator, which should be encouraged in both research and policy making. Moreover, as in the human well-being case, it is possible to replace F with different indicators of environmental impact. A future development of this research could indeed be a similar analysis replacing HLI and F with different indicators in Equation (4). In addition, country variables not considered here could be included in the future, such as innovation indexes, cultural dimensions, or biodiversity indicators.

6. Conclusions

Starting from the physical concept of efficiency, we introduced a novel indicator measuring the ability to achieve human well-being while limiting environmental impact. Even if the reduced data availability has partially limited the number of covariates included in our analysis, we were able to investigate the relation between ecoE and a broad set of variables encompassing different human dimensions (economic, political and demographic). Results clearly highlighted that demographic factors — especially population density and fertility rates — affect Ecological Efficiency more than any other variable, exerting a strong negative influence. This is further confirmed by the comparison between population growth and changes in ecoE (Fig. 4).

This result, for which we provided a possible explanation in Section 5, has important policy implications. In most countries, policy makers have as a main goal to foster economic growth, possibly adding measures to limit the resulting environmental impact. Demographic factors are instead often neglected or, when considered in policies (especially in wealthier countries), they usually aim to contrast aging by promoting higher birth rates (Gauthier, 2014; Tan, 2023), hence increasing fertility and population density. Rethinking these policies appears urgent since high population density and fertility are major hinders to ecological efficiency. In a world where a significant fraction of the global population is still poor and environmental crises are increasingly pressing, becoming ecologically efficient is not just an option but a necessity.

CRediT authorship contribution statement

Lucia Tamburino: Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing, Visualization. Giangiacomo Bravo: Data curation, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing.

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.

Data availability

The Supporting Information includes all details and code to reproduce the research. Data will be made available in the OSF repository after publication.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.indic.2023.100322.

References
