Assessing the energy vulnerability in small island developing states.

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ABSTRACT

Small island developing states (SIDS) suffer from several structural characteristics such as remoteness, small size, and the non-interconnection of networks that tend to jeopardize their ability to achieve energy transition. While this transition calls for structural changes in energy systems, SIDS are still heavily dependent on imported fossil fuels. We stress the importance of understanding the role of island energy systems in energy vulnerability, a complex and multidimensional phenomenon. The vulnerability of these territories to energy system disturbances and dysfunctions over which they have no control needs to be assessed. A composite index of energy vulnerability is constructed using a multilayer Data Envelopment Analysis (MLDEA) approach based on several energy indicators for 38 SIDS UN-members. We analyze the contribution of those dimensions that play an important role in energy vulnerability. Results suggest that inter- and intra-region disparities exist amongst SIDS when it comes to vulnerability assessment. On average, SIDS in the AIMS region have better energy performances than their island counterparts. We also identify policy priorities for each region following a cluster analysis and recommend inter- and intra-regional cooperation between these territories in terms of technology transfers and tailored solutions that better suit their specificities.

***Keywords**: Energy vulnerability; SIDS; composite index; energy security; Multi Layer Data Envelopment Analysis*

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1. INTRODUCTION

How to move away from fossil fuels and implement more renewable energy is one of the most pressing issues of this era. Indeed, an ongoing challenge for countries worldwide is to ensure the uninterrupted supply of energy in order to secure energy services for the population (Sovacool, 2013). Energy plays a vital role in economic growth and development as it is a significant input to fuel economic and social activities. On the other hand, the combustion of fossil fuels is largely responsible for the deterioration of the atmosphere due to the accumulation of carbon dioxide (CO_2) and other harmful gases. Kemmler and Spreng (2007) depicted energy as the ultimate commodity and at the same time the ultimate pollutant, warning the contradiction in its use and the resulting consequences. Governments worldwide put this strategic good on the front burner (Patlizianas et al., 2008; Böhringer and Bortolamedi, 2015), calling for sound management and planning.

In this study, we consider the energy challenges that SIDS and other island territories faces as regards their respective energy systems. These territories are already afflicted by several structural handicaps such as small size, remoteness, and the non-interconnection of networks that jeopardize not only put strain on their economic prosperity (Briguglio, 1995; Adrianto and Matsuda, 2004; Garabedian and Hoarau, 2011; Blancard and Hoarau, 2013) but also their ability to ensure a sustainable energy future. While energy transition calls for structural changes in energy systems, i.e., moving away from fossil fuels and deploying more renewable technologies, the extensive reliance of SIDS and other island territories appear as one of the most challenging issues they must face since most of them are not endowed with fossil energy resources. As a result, these territories are even more exposed to external disturbances such as energy price volatility and disruption risks in their energy supply chains. Understanding the consequences of such disruptive events becomes an essential part of energy planning and management to design adequate strategies and tailored solutions that would address key energy challenges. In other words, identifying selected adverse events that render the latter vulnerable and insecure from an energy viewpoint is a first step towards ensuring a sustainable energy future for their population.

Energy vulnerability and (in)security concerns, both intertwined in their definitions, are not new. Energy security is seen as the "low vulnerability of vital energy systems" (Guivarch and Monjon, 2017, p. 530). Substantial literature dedicated to the study of these phenomena bear witness of their relative importance to economies worldwide. Energy security has no universally accepted definition since the analysis of such complex and multidimensional phenomenon is context-dependent. Winzer (2012) found over 30 definitions of energy security (ES) and argued that the underlying common notion to all was the absence of protection or adaptation to threats caused by the energy supply chain. Although ES has historically focused on energy (in)dependence, especially after the world's first energy crises in the 1970s, recent concerns include (environmental) sustainability and the continued supply of energy services to the population at an affordable cost. As such, recurring dimensions encountered in the literature are accessibility (i.e. access to energy and access to clean fuels and technologies), affordability (i.e. supply of energy services at affordable prices) and availability (i.e. ensuring that energy is physically available in adequate amount) amongst others (APERC, 2007). Following threats that could potentially be disruptive to an economy's proper functioning, governments and researchers have proposed several methods to capture energy vulnerability and (in)security such as energy modelling or composite indices.

In this study, we focus on composite indices for their simplicity and transparency, and above all their ability to capture the complexity and multidimensionality of energy vulnerability and (in)security. Several authors have proposed ES and energy vulnerability indicators, and constructed composite indexes over time (Percebois, 2007, d'Artigues, 2008; Gnansounou, 2008;

Sovacool and Mukherjee, 2011). However, a literature review on energy vulnerability suggests there exists only a handful of studies focusing on this phenomenon with no universally accepted definition that date back to the 2007-2012 period. We argue that past and current research have not given sufficient consideration to SIDS and other island territories when it comes to constructing a meaningful composite index to capture the complexity and multidimensionality of energy vulnerability. Most studies focus on industrialized nations (Sovacool, 2013). To date, few studies exist on energy vulnerability and (in)security in SIDS and other island territories (Wolf et al., 2016; Raghoo et al., 2018). This paper therefore adds to the thin literature on the subject with the objective to better understand the critical energy challenges these territories are faced with.

Percebois (2007) proposed several indicators to characterize the phenomenon: energy import concentration, energy bill, technical options, black-out risks, energy intensity of gross domestic product (GDP) amongst others and gave a very broad definition of energy vulnerability: '[…] the unbearable dimension of energy supply' (p.51). However, no composite index was computed based of these selected indicators, thereby weakening the reliability of this specific set of indicators. Gupta (2008) used the concept of energy vulnerability to measure the energy vulnerability of net oil importing countries, thereby focusing on only one single source of energy (oil products). We argue that energy vulnerability encompasses oil dependency, although this aspect is still relevant in vulnerability studies nowadays. Gnansounou (2008) also assessed the phenomenon for 37 industrialized countries based on several energy dimensions and derived a composite index of energy vulnerability by computing the square root mean of the five sub-indicators. Once again, SIDS and other island territories were left out of the study.

An interesting approach was introduced by d'Artigues and Vignolo (2012) who suggested a systemic approach to measure energy vulnerability. It comprises of three main components that are exposure (i.e. the frequency, the degree and duration of possible disturbances), sensitivity (i.e. the degree to which the system can be modified or affected by shocks) and adaptive capacity (also known as resilience, described as the ability of the system to adapt or adjust to disruptions and to mitigate the consequences of the transformations that appear). D'Artigues and Vignolo (2012) selected the energy mix diversity as an indicator of the exposure component, arguing that a well-diversified energy mix is generally seen as a bulwark against uncertainty. The energy consumption per capita was chosen as a proxy for the sensitivity since a system will be even more affected as its consumption keeps rising. Finally, the rate of learning, and Research, Development and Demonstration (RD&D) were selected to capture the adaptive capacity of a country. RD&D is believed to mitigate the importance of exposure and sensitivity.

We decide to build on d'Artigues and Vignolo (2012) approach to frame energy vulnerability. In this study, energy vulnerability comprises two main components: exposure and (sensitivity to) shocks. We choose to leave out the adaptive capacity of SIDS and other island territories. Energy vulnerability is thus defined as the degree of sensitivity of an energy system to external threats (outside the energy system) causing disturbances (supply chain disruptions or energy price volatility) or internal dysfunctions (within the energy system) related to technology availability for the production, transmission and distribution of energy. The exposure component essentially captures the extent to which these territories are fragile/sensitive to potential threats (adverse events). On the other hand, the shock component accounts for the possible transformations these territories will undergo following a specific shock. Energy vulnerability thus hinders the ability of a country to provide vital energy services to its population and meet energy needs at affordable prices following internal or external disturbances. Selected indicators are thus related to the structural aspects of energy vulnerability over which countries have no control. They are independent of political orientations put in place in these territories.

Merely quantifying the extent to which SIDS and other island territories are energy vulnerable would not be meaningful on its own unless a comparison between these territories is operated. We find that disparities not only exist between AIMS, Caribbean and Pacific regions but within each region. We used a multilayer data envelopment analysis (MLDEA) to compute the composite index of energy vulnerability. The MLDEA framework proposed by Shen *et al.* (2013) allows for endogenous weighting scheme and is considered more robust than traditional schemes such as equal weighting. Indeed, countries are assigned a set of weights which put them in the best possible position, thereby limiting countries' protests on unfair or subjective weighting schemes. MLDEA, contrary to standard DEA models applied to index construction (called 'BOD-DEA') allows for more discriminating power between scores obtained by countries, making country rankings more straightforward. We show that the composite index of energy vulnerability can be a powerful and useful tool for SIDS and other small territories to identify strengths and weaknesses as well as benchmarking best practices in terms of good energy performances.

We applied a hierarchical clustering on principle components to the multivariate data set as a complementary analysis to MLDEA. The objective of the cluster analysiswas to highlight the heterogeneity of the countriesgroup them based on (dis)similarity in terms of energy performances. Of the 38 SIDS and island territories under investigation,a total of five optimal clusters were derived. We analysed the strengths and weaknesses of each group and made specificpolicy recommendations. The leaders identified under MLDEA were clustered together, indicating consistency with MLDEA results. On the other hand, Trinidad and Tobago appeared as a singleton, suggesting major differences from its island counterparts.

The remainder of this paper is organized as follows: Section 2 describes how the energy vulnerability index (EnVI) is constructed. The selection of dimensions (and relative indicators) along with index construction steps are also detailed in this section. Simulated results are provided in Section 3 followed by a discussion. Section 4 concludes and provides key recommendations for SIDS and other island territories.

2. METHODOLOGY

2.1 Data set description

2.1.1 Data

The energy vulnerability index was computed for 38 territories (with 36 SIDS UN-members along with Madagascar and Reunion Island located in the Indian Ocean) for the year 2015, for which most recent data were available. These territories are grouped into three main regions: AIMS, Caribbean and the Pacific. Initially, we intended to use the complete list of SIDS UN-members but data for all indicators were not available for Marshall Islands and Nauru. The list of countries under investigation can be found in Appendix A. Several databases were used to collect information on each territory and were mostly retrieved from the United Nations Statistics Division data sets and The World Bank. Data on CO_2 emissions were extracted from the Emission Database for Global Atmospheric Research[2](EDGAR) (Olivier et al., 2016). All indicator data sources are reported in Appendix B.

[2] Emission Database for Global Atmospheric Research (EDGAR)informs researchers and decision makers on the evolution of the emission inventories over time for countries worldwide (edgar.jrc.ec.europa.eu).

2.1.2 Selection of indicators

The main goal of this paper is to assess the relative energy vulnerability of AIMS islands as regards the energy performance of other island territories and SIDS in the Caribbean and the Pacific. The first step is to identify a proper framework for energy vulnerability (Nardo *et al.*, 2008; Luzzati and Gucciardi, 2015).Following the definition given earlier,energy vulnerability is thus seen as a potential threat to the sustainable energy future of these territories if nothing is done to mitigate such vulnerability.The next step is to select indicators that best capture energy vulnerability by means of a multivariate analysis. Potential indicators were identified using the energy indicators for sustainable development (EISD)[3] proposed by the International Atomic Energy Agency along with other international organizations (IAEA, 2005), and existing literature on energy security and vulnerability (Gnansounou, 2008; Gupta, 2008; Iddrisu and Bhattacharyya, 2015; Narula and Reddy, 2016; Raghoo *et al.*, 2018).

A Principal Component Analysis (PCA) is then used to identifyuncorrelated indicators which cover several dimensions such as availability, affordability, (environmental) sustainability amongst others. The chosen indicators are categorized as social, economic and environmental.The initial set of 21 variables is reduced to a final set of eight indicators which explain more than 50% of variances in the dataset (see Fig. C.2 and Table C.2 in Appendix C).Given this information, Figure 1 presents a four-layer hierarchical structure for the energy vulnerability concept. The first layer is composed of the eight indicators. The second layer containsfourdimensions (two under the exposure sub-index and two others under the shock sub-index) while the third layer is composed of twosub-components(exposure sub-index and shock sub-index).The fourth and final layer (EnVI) is obtained by aggregating the two sub-components.It should be noted, however, that in this study, the composite index should be interpreted as an index of non-vulnerability since DEA computes efficiency scores (i.e. the higher the better). As a result, we have been careful to standardize all indicators accordingly using the min-max procedure. The table of standardized indicators is given in Appendix D.

[3] The EISD publication resulted from a joint effort made by the International Atomic Energy Agency in collaboration with the United Nations Department of Economic and Social Affairs (UNDESA), the International Energy Agency (IEA), Eurostat and the European Environment Agency (EEA).

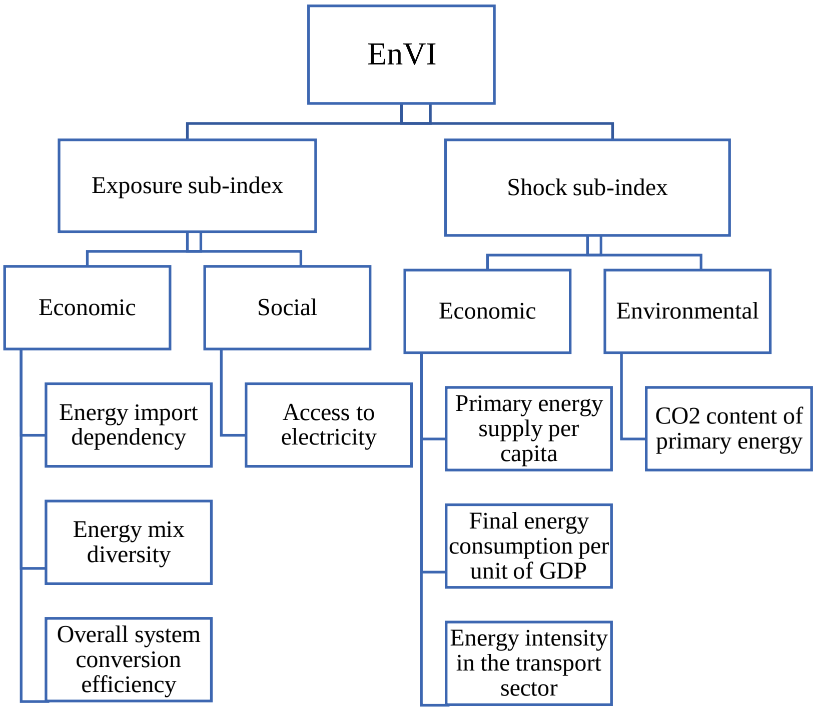

Fig. 1 Hierarchical structure of the composite index of energy vulnerability (EnVI)
Source: authors

EnVI dimensions and relative indicators:

1) Economic vulnerability

Indicators belonging to this dimension give an indicationof energy use (IAEA, 2005). They represent potential market (economic) and supply risks that can result in 'larger macroeconomic adjustment costs' following energy price volatility, especially in oil markets (Gnansounou, 2008, p.1197). Increases in energy prices combined with supply disruptions lead to disastrous effects on small economies. Moreover, a highly (oil) concentrated primary energy mix would result in greaterexposure to exogenous shocks on international energy markets for SIDS and other island territories.

- *Primary energy supply per capita (ECO1)*

Primary energy supply per capita indicates the level of primary energy physically available for consumption. It also gives an indication of how sensitive an economy is to a shock (for instance supply disruptions or fluctuations in energy prices) that would directly affect the level of energy end-users will consume. Per capita primary energy supply varies between 0.15 toe/cap for Timor-Leste and 14.27 toe/cap for Trinidad and Tobago. On average, SIDS and other island territories consumed 1.60 toe/cap in 2015.This indicator, combined to other useful indicators such as energy intensity, gives valuable insights into the consumption pattern of SIDS and other island territories where most energy consumed is based on fossil fuels.

- *Final energy intensity of GDP (ECO5)*

Energy use per unit of GDP is a 'marker of aggregate energy intensity'(IAEA, 2005, p.18). It provides valuable insights into a country's ability to monitor energy efficiency (reciprocal of energy intensity) when the structure of the economy is included in the analysis. Indeed, two countries with opposite economic structures might both achieve a low energy intensity. An economy although enjoying a high level of GDP while using less energy (energy efficient economy) will have a low energy intensity. The same will be achieved by a less developed country with a relatively low level of GDP whose domestic energy demand is relatively low. All in all, energy intensity of GDP is one of the most used energy indicators in security and vulnerability assessment. Monitoring energy intensity over time gives a good indication of whether countries have been successful or not in engaging in energy transition, i.e., using less energy to achieve the same level of GDP. Final energy intensity of GDP is obtained by dividing the total final consumption by GDP.The average energy intensity for the group in 2015 was 0.085 toe/$1000 PPP.

- *Energy intensity in the transport sector (ECO10)*

Emissions from the transport sector account for over 20% of total global CO_2emissionsin 2016 with more than 90% of world energy transportation based on fossil fuels (IEA, 2018). This sector is therefore one of the most polluting sectors for all countries under investigation. Capturing energy intensity in this sector therefore gives useful insights into how efficiently SIDS and other island territories use energy. It indicates to what extent the transport sector depends on primary energy as an input.The higher the energy intensity, the more energy is needed to fuel the transport activities, and the more vulnerable the country will be. A high score in this dimension suggests SIDS should diversify their transport energy mix with indigenous sources. As pointed out by Gupta (2008), non-diversity in transport fuels renders countries more vulnerable. Energy intensity in the transport sector is obtained by dividing total energy use by the sector's total gross value added (GVA).The Federated States of Micronesia had the most energy intensive transport sector for 2015with a ratio of 2.06 toe/$1000 GVA.

- *Energy import dependency (ECO13)*

Energy import dependency is a critical issue for SIDS and other island territories since most of them rely extensively on imported fossil energy for their primary energy supply. As identified by Raghoo *et al.* (2018), this is the most important issue for SIDS based on a survey carried out in these territories to identify the most challenging energy issues. Percebois (2007) and Gnansounou (2008) also proposed this dimension in their studies. Disruptions in primary energy supply could negatively affect economic activities and have disastrous impacts on economic growth in the long-run (Bhattacharyya, 2011), thereby worsening their exposure to external shocks. Singapore was the most energy dependent island in 2015 while Guinea-Bissau was the most autonomous in terms of fuel imports. Energy import dependency is obtained by dividing fuel imports by total primary energy supply. Data is obtained from the United Nations Energy Balances for the year 2015.

- *Energy mix diversity (ECO14)*

Both the primary and secondary energy mix of SWIO islands are still characterized by heavy use of carbon-rich fossil fuels (coal and petroleum). Diversification of the local energy mix is believed to be a key strategy in anticipating major disruptions in primary energy supply. Not only does diversification matter but the extent to which the energy mix is diversified is even more important. For instance, Mauritius has a relatively diversified energy mix for electricity generation but is still highly dependent on fossil fuels, although there is political will to transition to cleaner energy sources and technologies. Two methods are extensively used in the literature to analyse the diversity (or concentration) of energy mixes: the Shannon-Wiener

(SW) diversity index or the Herfindahl-Hirschman (HH) concentration index. Several studies use this metric (or a modified version) to assess fuel diversity (APERC, 2007; Jansen, Arkel and Boots, 2004). The HH index is essentially used when assessing market concentration of suppliers. The SW index is used in this paper to assess the diversity of domestic energy mixes in countries under investigation. The SW diversity index is computed as follows:

$$SWI = -\sum p_i \ln (p_i)$$

Where p_i is the share of fuel type$i$ in the primary energy mix.Reunion Island had the most energy diversified mix in 2015 followed by Mauritius in that year. Those islands that rely solely on a single source of energy have a SW index equivalent to zero. This was the case for Antigua and Barbuda, as well as Palau.

- *Overall system conversion efficiency (ECO16)*

An efficient system conversion captures the ability of the energy supply system to meet the present and future needs of society reliably, efficiently and from clean sources. The overall efficiency of the system conversion is thus obtained by dividing total final energy consumption (TFC) by total primary energy supply (TES). The higher the conversion efficiency, the less energy is lost during conversion, and the less energy vulnerable will the country be since less energy is required to satisfy the same level of useful energy, i.e. total final consumptionrequirement (Iddrisu and Bhattacharyya, 2015).The TFC/TES ratio was highest for Guinea-Bissau, making it the most energy-efficient territory.

2) Environmental vulnerability

Environmental considerations cannot be ignored when assessing the ability of a country to engage in energy transition. Small economies face environmental risks (mainly climate change and global warming) due to an increased usage of fossil fuels.

- *Carbon content of energy (ENV3)*

Climate change is already disrupting economic, social and environmental prospects worldwide. SIDS and other island territories are being impacted more severely by extreme weather events like tropical storms, sea-level rise and rising temperatures. Carbon dioxide (CO_2) released from the combustion of fossil fuels contribute to global warming and climate change. As such, energy transition calls for the phasing out of carbon-based fuels. A high score in this dimension indicates that a country is vulnerable from an energy viewpoint since countries relying extensively on fossil fuels would be more vulnerable to future energy and climate policies like carbon taxes and carbon caps. Average CO_2 emissions amounted to 5000 kilotons of CO_2 equivalent (kton CO_2) for the group in 2015, ranging from a minimum of 1 kton CO_2 for Tuvalu to a maximum of 47000 kton CO_2 for Singapore. ENV3 is obtained by dividing total CO_2 (kton CO_2) emissions by TPES (Ktoe).

3) Social vulnerability

- *Access to electricity (SOC1)*

Access to electricity in island states and territories varies greatly (Wolf et al., 2016; Surroop and Raghoo, 2017; Raghoo et al., 2018). This dimension is particularly contrasted in the ACP regions. Indeed, islands like Comoros and Madagascar still struggle to provide universal access to their population. This represents a huge challenge that local authorities have yet to overcome. Indeed, access to energy varied between 14% for Guinea-Bissau and 100% for only seven SIDS in 2015.Availability of energy is an important aspect to consider since it impacts poverty and other social dimensions. This has been particularly highlighted by the United Nations' sustainable development goal (SDG) 7 which pursues the provision of affordable, reliable, sustainable and modern energy services for all (United Nations, 2015). Access to electricity is captured by the proportion of people having access to electricity. The higher this proportion, the lower the energy vulnerability of SIDS and other island territories. Although it is debatable whether a country with a lower access rate is less vulnerable since the latter would have a lower energy demand and thus be less vulnerable to energy disruption risks or price fluctuations.

2.2 The DEA framework

Once the identification of energy vulnerability indicators has been operated, the second stage of this study involves summarizing the information they provide into a unique value. In our case, energy vulnerability is expressed as the weighted average of all vulnerability dimensions for a selected country in terms of each indicator. Formally, we assume that we have information for J countries about s indicators used to describe energy vulnerability in the AIMS, Caribbean, and Pacific regions, which allows the computation of a composite indicator (CI). The respective index sets of countries and indicators are defined as $j=(1,\ldots,J)$, $r=(1,\ldots,s)$. Let y_{rj} denote the value of country j with respect to indicator r. Let w_{rj} also be the weight associated to indicator r for the country j. We seek to aggregate y_{rj} into a CI for each country $j$as follows:

$$\mathrm{CI}_j=\sum_{r=1}^{s} w_{rj} y_{rj}, \quad j=1,2,\ldots,J \tag{1}$$

Our challenge thus consists in the determination of the weights required to construct the composite indicator. Several weighting methods exist. We can separate them between methods based on statistical models (e.g. the principal components/factor analysis, the unobserved components model and the regression analysis) and those based on public/expert opinion (e.g. the budget allocation process, the conjoint analysis and the analytic hierarchy process). In the first category of models, we also find the DEA approach. Compared to other methods, DEA methodology initially proposed by Charnes *et al.* (1978) and the related models present some advantages. It avoids subjectivity since it does not rely on expert judgment and public opinion polls but is solely based on the data. This is particularly useful when dealing with composite indices which are generally characterized by uncertainty and lack of consensus on an appropriate weighting scheme. Thus, countries cannot claim that poor relative performance is due to an unfair weighting system, as the method selects weights that maximize the composite index for each country under investigation (Zhou *et al.*, 2007). Inversely, the DEA method allows each country to use the weights which place him in the best possible position in accordance with the principle benefit of the doubt (Melyn and Moesen, 1991). Therefore, contest by countries on the weights is less unlikely (Cherchye *et al.*, 2007).

Beyond the advantages of DEA, some points inherent to the methodology deserve attention. First, DEA methodology is determinist which leads to a score sensibility to the problem of noise in the data (e.g. outliers' presence). Some additional developments maybe necessary to get rid of the problem in order not to affect the robust results[4]. Second, the score obtained by a country reflect a relative energy vulnerability in relation to the rest of sample. Hence, a country with score equal to unity is maybe vulnerable in absolute. In order to consider this second element, we can imagine other vulnerability measurements from samples that should integrate other countries or group less vulnerable in absolute. This allows us to appreciate the real position of our group of 38 territories in the AIMS at a different scale.

Among the DEA literature, several proposals have been made (see Zhou *et al.*, 2007; Cherchye *et al.*, 2007 or more recently Rogge, 2018). Given the hierarchical structure of the energy vulnerability composite index, we opt for the multilayer DEA (MLDEA) model. Initially introduced by Meng *et al*. (2008), often referred to multi-level DEA models, and linearized in the same year by Kao (2008), its usefulness to build composite indicators is due to Shen *etal.* (2013). Shen *et al.* (2013) state that the MLDEA model has more discriminating power than standard BOD-DEA like models. Moreover, the most important feature is thought to be the architecture of the model, that suits to studies involving multidimensional phenomena where hierarchical structures need to be explicit.

2.2.1. The DEA model in the field of composite indicators

In the basic DEA model originally proposed by Charnes et al. (1978), the objective is to maximize the efficiency value of an entity, from among a reference set of entities by selecting the optimal weights associated with the input and outputs. In the field of composite indicators, the basic DEA model is an output maximizing multiplier DEA model with multiple outputs (i.e. indicators) and constant inputs in which the different outputs level (or indicator level) and a single dummy input with value unity is assigned to each country.

Let J be the number of countries evaluated in terms of s indicators. The respective index sets of countries and indicators are defined as $j = (1,\mathrm{K}\ , J)$, $r = (1,\ldots,s)$. For a country o, the basic DEA model for composite indicators can be formulated as follows:

$$\begin{aligned}
&\mathrm{CI}_o = \max \sum_{f_1=1}^{s} \hat{u}_r y_{ro} \\
&\text{subject to} \\
&\sum_{r=1}^{s} \hat{u}_r y_{rj} \leq 1, \ \ j = 1,\ldots, J \\
&\hat{u}_r \geq 0, \ r = 1,\mathrm{K}\ , s
\end{aligned} \qquad (2)$$

where:

CI_o : the value of composite indicator (CI) of the evaluated entity o;
$\hat{u}_r$: the weight assigned to indicator r for evaluated entity o;
y_{rj} : the value of indicator r of entity j.

For the evaluated country o, the model (2) estimates the weights $\hat{u}$ that maximize theweighted sum of indicators and it is solved for one country at a time. In other words, for each country, this

[4] A non-technical but comprehensive overview concerning noise, uncertainty and measurement issues in DEA can be found in Dyson and Shale (2010).

model seeks the best set of weights which are used to aggregate the indicators into a composite index. The first restriction guarantees that no country can be obtain a score larger than unity under these weights.The second constraint is introduced to assure that none of the weights will take a zero value[5]. The value on this composite index is therefore bounded in the interval [0,1]. Countries that achieve a score equal to unity are considered as the least energy vulnerable among the sample. Respectively, if the score is lower than unity the countries might be considered as the most energy vulnerable. The lower the score, the higher the vulnerability.

2.2.2. The Multilayer DEA Model

Now, introduce additional information about hierarchical structure on the composite index. Let *n* be the number of countries evaluated in terms of *s* indicators with a *K* layered hierarchy. The respective index sets of countries, indicators and layers are defined as $j=(1,\ldots,J)$, $r=(1,\ldots,s)$ and $k=(1,\ldots,K)$. Let also $f_k=1,\ldots,s^{(k)}$ be the *f*th category in the *k*th layer where $s^{(k)}$ is the number of categories in the *k*th layer. $s^{(1)}=s$, i.e. the number of categories in the first layer is equal to the number of indicators. $y_{f_k j}$ represents the value for country *j* on the indicators of the *f*th category in the *k*th layer. For a country *o*, the MLDEA model can be formulated as follows:

$$
\begin{aligned}
&\mathrm{CI}_o = \max \sum_{f_1=1}^{s} \hat{u}_{f_1} y_{f_1 o} \\
&\text{subject to} \\
&\sum_{f_1=1}^{s} \hat{u}_{f_1} y_{f_1 j} \le 1, \quad j=1,\ldots,J \\
&\hat{u}_{f_1} \ge 0, \; f_1 = 1,\ldots,s^{(k)}
\end{aligned}
\tag{3}
$$

where:

$\hat{u}_{f_1}$	:	set of optimal weights assigned to the indicators of the *f*th category in the first layer for country *o* obtained by solving model;
$y_{f_1 j}$ and y_{f_1}	:	the value for country *j* and *o* respectively, on the indicators of the *f*th category in the first layer;
$s^{(k)}$	:	number of categories in the *k*th layer ($k=1,2,\ldots,K$).

At this stage, for the evaluated country *o*, the model (3) estimates the weights $\hat{u}$ that maximize the weighted sum of the categories in the first layer. Since $s^{(1)}=s$, this model (3) is similar to the DEA model (2) *i.e.* the hierarchical structure of composite index is not yet considered. To do that, specifying the importance of the weights in each category of each layer and limiting their flexibility are necessary. Fortunately, the model (3) is sufficiently general to allow consideration of additional restrictions on the weights[6]. Following Shen *et al*. (2013), we consider upper and lower limits on corresponding to the internal weights associated with indicators of the *f*th category

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[5] Without more restriction on weights, the composite index represents the lower bound on vulnerability given the optimal set of weights assigned to each country.

[6] Several ways exist for integrating restrictions on sub-indicator shares. For a presentation of these approaches or an examination of the role that can play the restriction in DEA, we can refer respectively to Cherchye *et al*. (2007) and Pedraja-Chaparro *et al*. (1997).

in kth layer, which sum to unity within a particular category [7]. Formally, we have $\sum_{f_1 \in A_{f_k}^{k}} \hat{u}_{f_1} \Big/ \sum_{f_1 \in A_{f_{k+1}}^{(k+1)}} \hat{u}_{f_1}$ where $A_{f_k}^{(k)}$ is the set of indicators of the fth category in the kth layer. By adding this restriction on weights in the model (3), the model is now written as follows:

$$
\begin{aligned}
& CI_o = \max \sum_{f_1=1}^{s} \hat{u}_{f_1} y_{f_1 o} \\
& \text{subject to} \\
& \sum_{f_1=1}^{s} \hat{u}_{f_1} y_{f_1 j} \leq 1, \quad j = 1, \ldots, J \\
& L \leq \frac{\sum_{f_1 \in A_{f_k}^{k}} \hat{u}_{f_1}}{\sum_{f_1 \in A_{f_{k+1}}^{(k+1)}} \hat{u}_{f_1}} \leq U \qquad f_k = 1, \ldots, s^{(k)};\ k = 1, \ldots, K-1 \\
& \hat{u}_{f_1} \geq 0,\ f_1 = 1, \ldots, s
\end{aligned}
\tag{4}
$$

where L and U represent the lower and upper limits imposed on corresponding internal weights, respectively. The main idea of this model is to aggregate the values of the indicators within a particular category of a particular layer by the weighted-sum approach in which the sum of the internal weights equals 1.

2.3 Cluster analysis

We also decide to perform a Hierarchical Clustering on Principal Components (HCPC) analysis using the “FactoMineR” and “factoextra” R packages. Since our data is multidimensional and contains multiple continuous variables, PCA helps to reduce dimensionality in the data set by removing ‘noise’ for more stability in clusters. We specify the number of final components to be kept (*ncp = 3*) and then apply the HCPC to the PCA results. The Ward’s minimum variance criterion is used to compute distance between clusters based on the Euclidean distance between points. At the beginning, each country forms a cluster by itself (works from bottom to top) and are gradually agglomerated to form meaningful subgroups (Fraley and Raftery, 1998).

To better visualize and interpret HCPC results, we generate a dendrogram (also called a ‘tree’) that graphically represents distances between clusters along the vertical axis (denoted by ‘height’). The algorithm determines the optimal number of clusters based on inertia gain in between and within-group clusters. Cluster analysis thus provides valuable insights in terms of energy practices in AIMS, Caribbean and Pacific regions so that SIDS and other island territories can identify benchmarks with greater similarity to their own relative energy performances.

[7] By imposing this restriction, we finally avoid that all the weight is carried over to a single indicator of each layer. Hence, it allows us the moderate the score value that could be obtained each country without constraint.

3. RESULTS AND DISCUSSIONS

3.1 Index score and country ranking

The eight normalized indicators (see Appendix D) are aggregated into a composite index of energy vulnerability. Results of the MLDEA (program (4)) are given in Table 1, along with the scores obtained under the standard DEA (a single-layered model). Note that MLDEA results only reflect relative vulnerability since the performance of a country is benchmarked on other countries' performances in the dataset. Table 1 shows that MLDEA has a higher discriminating power than standard DEA since only two countries, Reunion and Tuvalu, had the optimal score of one.Under the standard DEA, 29 countries obtained the optimal score, making it difficult to interpret their relative energy vulnerability. The Federal State of Micronesia had the worst energy performance with a score of 0.705 under MLDEA. Figure 2 reports the final values of EnVI for all SIDS and other island territories. Countries are ranked from most vulnerable (index scores between 0.7 and 0.8) to least vulnerable (index scores greater than 0.9).

MLDEA scores for underperforming countries are slightly lower than those obtained under the standard DEA model. Reunion and Tuvalu can thus act as benchmarks for underperforming countries to learn from best practices in these two territories. Caution should be paid when interpreting results. Reunion and Tuvalu are less vulnerable than other SIDS and island territories. An optimal score of one under MLDEA represents a lower bound on vulnerability given the optimal set of weights assigned to each country.

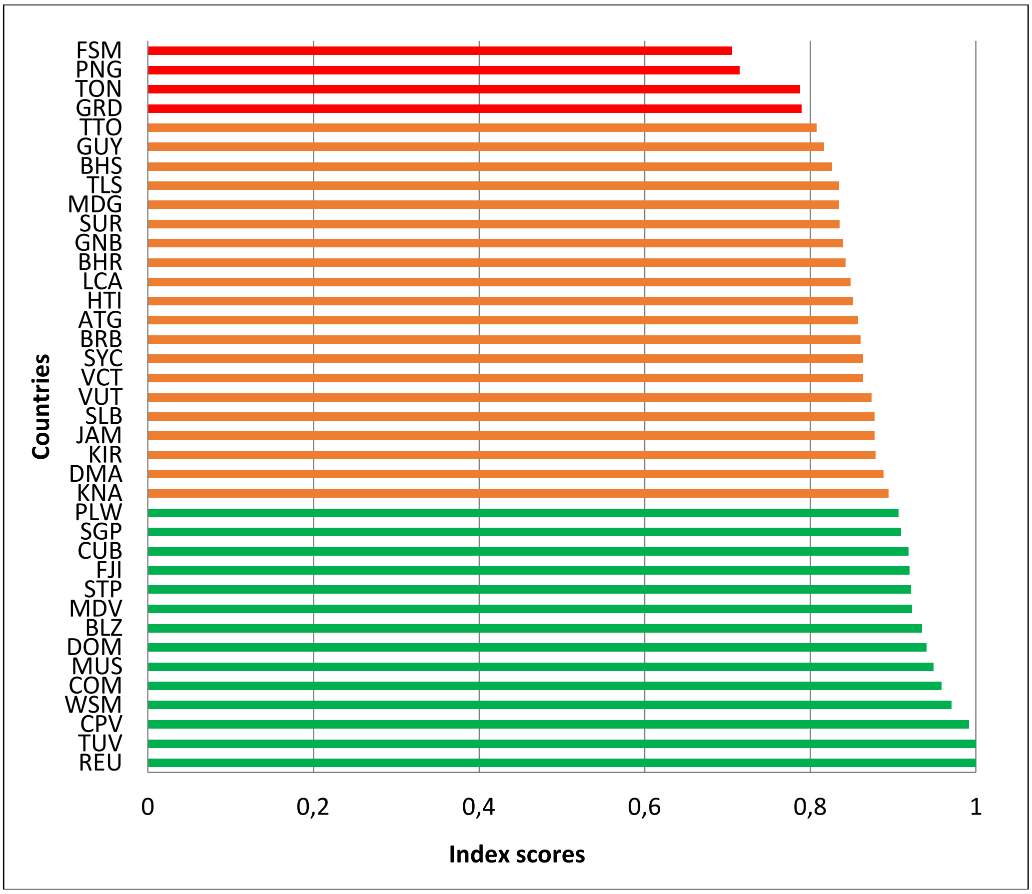

Fig. 2 EnVI scores from most vulnerable (0.705) to least vulnerable (1)
Source: authors

Sensitivity analysis was carried outto investigate country rankings under different weighting schemes (equal weighting). Different aggregating techniques were also tested. Results of the sensitivity analysis are reported in Appendix E. Overall, country rankings under MLDEA do not differ much from rankings under other weighting schemes and aggregation techniques (PCA) for the best and worst performers. However, we insist on the fact that MLDEA puts SIDS and other island territories in their best positions in ranking terms considering their relative energy performances. The set of weights, determined endogenously based on each country's relative performance, reveal policy priorities that these territories could use to define trade-offs. For those countries obtaining less favourable scores under MLDEA, the composite index acts as an incentive instead of a punishment for lagging countries to improve overall performance. This is the case for Timor-Leste and Madagascar which lose 18 and 16 places respectively. However, MLDEA provides useful benchmarks for lower ranking countries based upon a linear combination if observed best performances. Overall, SIDS and other island territories did not appear to be highly vulnerable from an energy viewpoint. Out of the 11 islands and territories in the AIMS region, six of them ranked in the top 10 best performing countries.

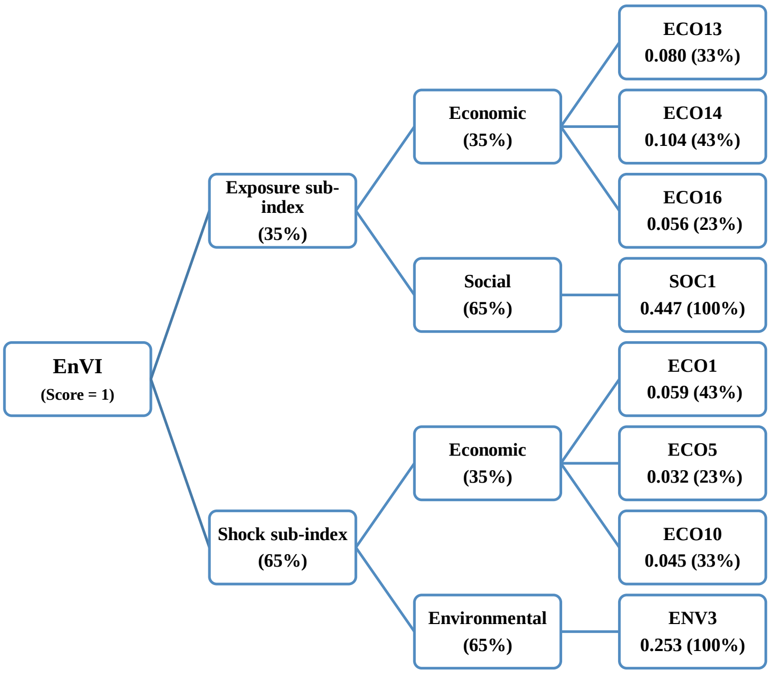

Fig. 3 Weights (and shares) assigned to Reunion Island
Source: authors

Figure3 provides valuable insights in terms of indicator weights in each layer of the hierarchy for a country (in this case Reunion Island). MLDEA guarantees that realistic and acceptable weights are assigned to each indicator by restricting the weight flexibility in each category of each layer (Shen *et al.*, 2013). This holds for every SIDS and island territory in the dataset. Weighting schemes are specific for each country and allow room for improvements by means of public policies. Thus, more weight is allocated to those indicators under which a specific country performs relatively well (and vice-versa). Dimensions requiring improvements are those assigned with less weights. Considering the case of Reunion Island, although being the least vulnerable island from an energy viewpoint, the island still needs to provide substantial efforts on the economic dimensions in both exposure and shock components. Indeed, they were assigned the lowest set of weights compared to the social and environmental dimensions. Shares in brackets are determined according to the degree of variability imposed to the model (here 30%). For instance, the contribution of 35% and 65% by the exposure sub-index and exposure sub-index respectively act lower and upper bounds.

Table 1 Results of program (4)

SIDS	DEA-Score	MLDEA-Score	Rank MLDEA	W_{SOC1}	W_{ECO1}	W_{ECO5}	W_{ECO10}	W_{ECO13}	W_{ECO14}	W_{ECO16}	W_{ENV3}
ATG	0.964	0.857	24	0.324	0.133	0.172	0.093	0.076	0.041	0.058	0.214
BHS	1.000	0.826	32	0.411	0.073	0.104	0.135	0.074	0.052	0.096	0.168
BHR	1.000	0.842	27	0.439	0.034	0.064	0.049	0.102	0.055	0.079	0.273
BRB	1.000	0.860	23	0.443	0.121	0.093	0.065	0.079	0.056	0.103	0.150
BLZ	1.000	0.934	8	0.243	0.134	0.103	0.072	0.150	0.105	0.195	0.166
CPV	1.000	0.991	3	0.164	0.103	0.079	0.055	0.101	0.071	0.132	0.441
COM	1.000	0.958	5	0.163	0.190	0.102	0.146	0.131	0.071	0.101	0.236
CUB	1.000	0.918	12	0.451	0.087	0.061	0.114	0.105	0.057	0.081	0.141
DMA	1.000	0.888	16	0.454	0.113	0.087	0.061	0.106	0.057	0.081	0.140
DOM	1.000	0.940	7	0.443	0.091	0.118	0.064	0.103	0.056	0.080	0.147
FJI	0.981	0.919	11	0.456	0.112	0.086	0.060	0.106	0.057	0.082	0.139
GRD	0.995	0.789	35	0.414	0.131	0.101	0.070	0.097	0.052	0.074	0.163
GNB	1.000	0.839	28	0.184	0.094	0.051	0.073	0.114	0.080	0.148	0.405
GUY	0.967	0.816	33	0.252	0.126	0.097	0.068	0.156	0.109	0.203	0.157
HTI	1.000	0.851	25	0.176	0.096	0.051	0.074	0.142	0.076	0.109	0.410
JAM	0.977	0.877	19	0.438	0.123	0.094	0.066	0.079	0.055	0.102	0.152
KIR	1.000	0.878	17	0.325	0.173	0.133	0.093	0.058	0.041	0.076	0.215
MDG	1.000	0.834	31	0.189	0.090	0.049	0.069	0.152	0.082	0.117	0.387
MDV	1.000	0.922	9	0.444	0.120	0.092	0.065	0.080	0.056	0.104	0.149
MUS	1.000	0.948	6	0.446	0.087	0.113	0.061	0.104	0.080	0.056	0.141
FSM	0.978	0.705	38	0.265	0.117	0.090	0.063	0.164	0.115	0.214	0.145
PLW	1.000	0.906	14	0.460	0.060	0.046	0.032	0.083	0.058	0.107	0.257
PNG	0.979	0.714	37	0.192	0.168	0.129	0.091	0.155	0.083	0.119	0.209
REU	1.000	1.000	1	0.447	0.059	0.032	0.045	0.080	0.104	0.056	0.253
KNA	1.000	0.894	15	0.324	0.133	0.172	0.093	0.076	0.041	0.058	0.214
LCA	0.991	0.848	26	0.441	0.092	0.119	0.064	0.103	0.055	0.079	0.148
VCT	1.000	0.863	21	0.427	0.128	0.098	0.069	0.077	0.054	0.100	0.159
WSM	1.000	0.970	4	0.454	0.116	0.089	0.062	0.082	0.057	0.106	0.144
STP	0.998	0.921	10	0.165	0.189	0.102	0.145	0.133	0.072	0.102	0.234
SYC	1.000	0.863	22	0.457	0.062	0.115	0.088	0.082	0.057	0.107	0.143
SGP	1.000	0.909	13	0.261	0.108	0.200	0.154	0.033	0.061	0.047	0.249
SLB	1.000	0.877	18	0.153	0.201	0.108	0.155	0.095	0.066	0.123	0.250
SUR	1.000	0.835	29	0.268	0.115	0.088	0.062	0.166	0.116	0.216	0.142
TLS	1.000	0.834	30	0.175	0.140	0.183	0.098	0.141	0.076	0.108	0.227
TON	1.000	0.787	36	0.399	0.140	0.108	0.075	0.072	0.050	0.093	0.174
TTO	1.000	0.807	34	0.385	0.041	0.059	0.077	0.090	0.048	0.069	0.328
TUV	1.000	1.000	1	0.274	0.144	0.101	0.188	0.064	0.034	0.049	0.233
VUT	1.000	0.873	20	0.162	0.195	0.150	0.105	0.100	0.070	0.130	0.243

Source: authors

3.2 Leaders and laggard

Reunion Island and Tuvalu scored the optimal score of one under MLDEA. They are therefore the group leaders since they outperformed other SIDS and island territories. It might be surprising however to get these two countries at the top since they differ in many ways, mostly from an economic point of view. Optimality should be understood here as a measure of best energy performances. Reunion and Tuvalu are no less vulnerable to internal and external disturbances. This gives an interesting insight into the energy transition efforts countries need to make and raises an important question: do all SIDS need to go through the same development stages in order to mitigate energy vulnerability and therefore accelerate energy transition? As such, indicator weights are useful in identifying dimensions that require improvements.

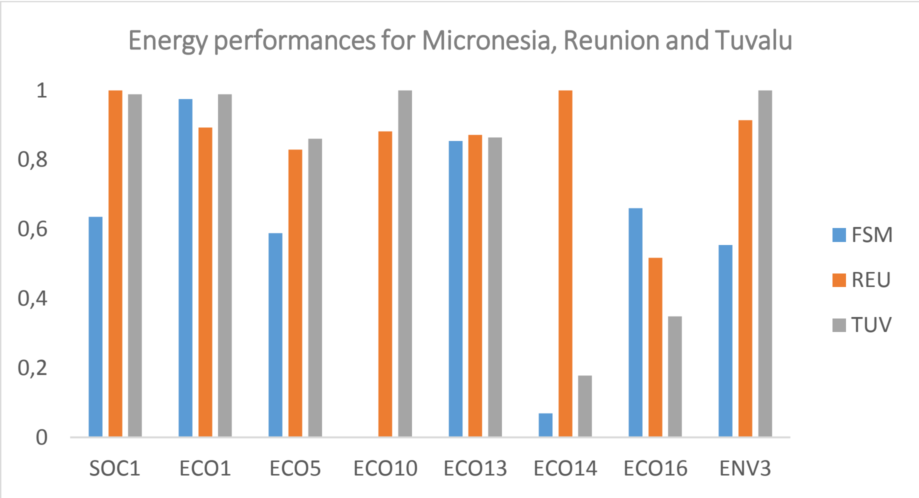

Fig. 5 Normalized indicator scores for Micronesia (FSM), Reunion (REU) and Tuvalu (TUV)
Source: authors

Reunion island enjoyed a high level of GDP but still relies extensively on energy imports of fossil fuels (with a dependency rate of 86%). A deeper insight was gained when decomposing the EnVI score and looking at the contribution of different dimensions to energy vulnerability. As already mentioned, Reunion performed best in the social and environmental dimensions, but efforts still need to be made as regards economic dimension, where relatively lower weights were assigned to each economic indicator. Under the shock sub-index, ECO5 was assigned a weight of 0.032 and ECO16 a weight of 0.056 under the exposure sub-index suggesting better resource allocation and more efforts directed towards improving the efficiency of converting primary into final useful energy. MLDEA is helpful in identifying policy priorities calling for actions in this particular dimension. However, as a leader, Reunion provides scope for progress for underperforming countries like Micronesia.

Tuvalu, categorized as a least developed country because of its limited scope for economic development, was also a leader. However, the island relied almost exclusively on imported fossil energy to power its economic activities, which is why it performed poorly on ECO14 (energy mix diversity). It was relatively less efficient than Reunion and Micronesia at converting primary energy into useful energy by minimizing losses during the transformation stage. Local authorities must focus on implementing more renewable technologies in their energy mix. The island highly depends on financial support from foreign countries could be diverted to the development of a carbon-free mix and the promotion of energy efficiency actions to improve system conversion efficiency (ECO16).

The Federated States of Micronesia (ranked 38th) was the least efficient island in terms of energy performances. Micronesia had a relatively high energy intensity of its transport sector and a highly concentrated energy mix. Relatively bad performances were recorded in 3 dimensions, namely access to electricity (69%), CO_2 content of TPES and final consumption per unit of GDP. It performed well in terms of energy consumption per capita. Following the case study, we conclude that while Micronesia is the most energy vulnerable small island, the gap between Micronesia and the leaders is not intractable. In view of results obtained, we suggest that Micronesia should focus on improving the energy efficiency of its transport sector (ECO16) by diversifying transport fuel for instance. Tuvalu could serve a benchmark for this dimension since both share the same geographic location (Pacific Ocean). Regarding its energy mix diversification strategies, Micronesia should consider Reunion Island as the reference country since the latter had the most diversified mix in the whole SIDS group.

3.3 Country clusters

Results of the HCPC suggest five clusters solution (Fig.4). The vertical axis represents (dis)similarity captured by the distance which accounts for differences between clusters. Identifying distinct groups of countries can be particularly useful in designing tailored energy policies. Five clusters are obtained as follows:

Group 1:	TTO
Group 2:	BHR; SGP
Group 3:	ATG; BHS; BRB; DMA; GRD; GUY; JAM; MDV; FSM; PLW; KNA; LCA; VCT; SYC; TON
Group 4:	GNB; HTI; MDG; PNG; SLB; VUT
Group 5:	BLZ; CPV; COM; CUB; DOM; FJI; KIR; MUS; REU; WSM; STP; SUR; TLS; TUV

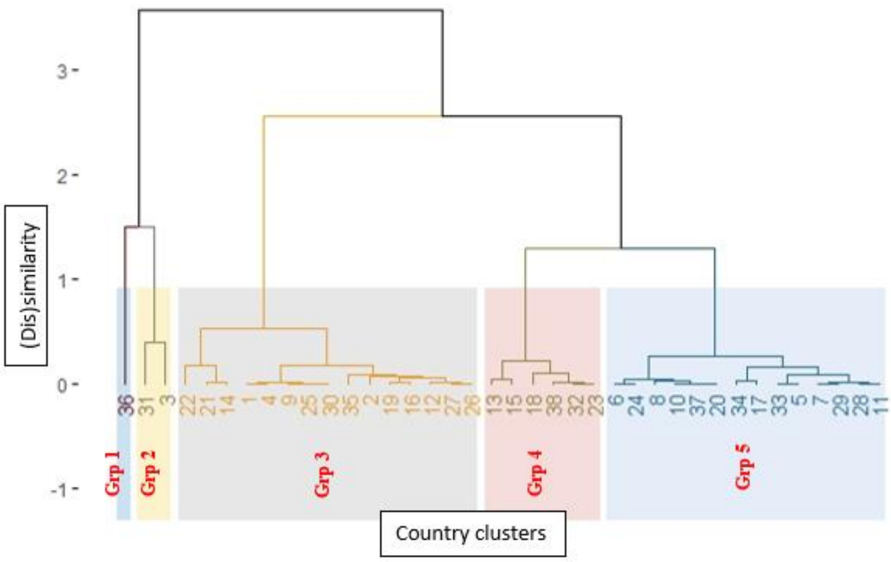

Fig. 4 Dendrogram with five optimal clusters
Source: authors

From figure 4, looking at height 1 on the (dis)similarity axis while moving horizontally across the x-axis indicates that five lines are crossed, resulting in the creation of five corresponding clusters. Numbers 1-38 on the horizontal axis refer to SIDS and island territories under investigation.

Trinidad and Tobago stand alone as a group. On average, it outperformed all other clusters in ECO13. This is not surprising as the latter is a net oil exporting country with a significant amount of domestic production, therefore accounting for a relatively lower energy import dependency rate. It also has the highest level of GDP per capita. The country however performed badly in ECO1 and ECO5. It had a highly concentrated energy mix, dominated by fossil energy. Moreover, Trinidad and Tobago are relatively less efficient in converting primary energy into useful energy.

Bahrain and Singapore form a cluster (Group 2). Bahrain is a net oil exporter. Although Singapore is a net oil importer, the latter also exports massively to other countries. The two islands also enjoy high levels of GDP per capita. Group outperformed all other clusters in ECO10 meaning that on average, these two have a lower energy intensity in the transport sector. However, a relatively bad performance in ECO16 indicates that the two islands are less efficient at converting primary energy into final energy for end-users. Group 3 had also a relatively bad performance in ECO13.

Most Caribbean islands are clustered in Group 3, indicating regional patterns in terms of energy practices and performances. On average, Group 3 recorded a relatively good performance overall except in ECO14. On average, this group has a relatively more concentrated energy mix than other clusters, dominated by imported fossil energy. Most SIDS and other island territories in this group had relatively high energy access rates.

Most Least Developed Countries (as identified by the United Nations Committee for Development Policy) are clustered in Group 4 except for Papua New Guinea. Overall, this group has a relatively low level of GDP per capita (Appendix A). This group reported relatively low rates of energy access. On average, they performed well in ECO13, meaning that they are relatively less energy independent than their island counterparts. This is mainly due to indigenous energy production. For instance, Guinea-Bissau is the least energy dependent of the whole group of SIDS and Madagascar also relies on local energy sources such as fuelwood to produce energy.

Group 5 clusters the top 10 performers under the energy vulnerability index (except Maldives who belongs to Group 3).The group recorded on average relatively good performances in all dimensions except for ECO16, suggesting islands belonging to this group are less efficient in converting primary energy into useful energy. Overall, best energy practices are recorded in this group (i.e. they on average less energy vulnerable than other clusters). Note that REU and TUV are in the same clusters (Group 5). This is understandable since HCPC is based on similar energy practices between SIDS and other island territories. MLDEA, on the other hand, allocates the best possible set of weights to islands under study. Since the objective of the study is to understand the extent to which these territories are vulnerable from an energy point of view, analyzing the contribution of different dimensions in determining energy vulnerability is important. Thus, REU and TUV are rewarded for their respective practices and act as leaders in Group 5. Readers should understand that while MLDEA helps to identify global benchmarks, the cluster analysis is seen as complementary. Thus, countries in other groups have a better understanding of which benchmark island is more suitable to learn from. Besides, this gives a valuable insight into island heterogeneity in terms of energy development pathways.

3.4 Policy implications for the five clusters

We use clusters identified earlier to derive group-wise policy implications based on their respective energy performances identified under MLDEA.

Trinidad and Tobago should focus on diversification strategies to reduce impacts of future shocks on its economy. Moreover, it had the highest energy consumption per capita and the highest energy consumption per unit of GDP. This should be interpreted with caution. On the other hand, Singapore enjoys higher levels of development than its other island counterparts while its energy consumption is higher, based on the island's economic structure. However, this could also mean that actual consumption patterns are not at all sustainable, and therefore puts much strain on the energy transition capacity of the island. Efforts should thus be directed at reducing energy use on the demand side by encouraging the deployment of energy efficient actions.

For Group 2 and 3, we suggest that priority should be given to lessening the economy's dependence on imported fuels, that is improving its self-sufficiency. The most energy dependent countries include Micronesia, Palau and Singapore. Fluctuations in energy prices, especially oil, can be disruptive not only from an economic viewpoint, but also from a political and social one. Indeed, an increase in fuel price resulted in social unrest in Reunion Island recently. On a more global scale, the concentration of oil reserves in a small number of politically unstable countries increases the risk for small economies to suffer from supply disruptions. Therefore, decision-makers in SIDS and other island territories are urged to maximize domestic sources of energy by substituting imported fossil fuels by indigenous energy sources such as hydro, wind and solar energy.

Islands in Group 3 should also focus on the diversification of their primary energy mix. Most countries in this group rely extensively dependent upon imported fossil energy to power their economic activities, especially Antigua and Barbuda, Bahamas and Palau. Disruptions in energy supplies would be catastrophic for them. To lowering their respective supply disruption risks, these islands should focus on developing local sources of energy.

For Group 4, we recommend priority be given to universal access to electricity and other modern energy services. Electricity networks thus need to be expanded to reach the whole population. Access to clean fuels and technologies should also accompany this policy package to ensure a sustainable future for the population economy-wide. SIDS and other island territories that are particularly targeted by this policy recommendation are Haiti, Madagascar and Papua New Guinea which had lowest electricity access rates of the whole group of 38 islands and territories.

We suggest that islands in Group 5 focus on their overall system conversion efficiency. Less efficient countries include Cuba, Mauritius, Timor-Leste and Tuvalu, accounting for higher transformation losses in turning primary energy into useful energy in 2015. Efforts can also be directed at the deployment of indigenous sources of production in order to diversify their respective primary energy mix.

4. CONCLUSION

In this study, we proposed a composite index to measure energy vulnerability in 38 SIDS and other island territories. No such index has been proposed for this special group before. We suggest that energy vulnerability is a combination of two components – exposure and shock - that both capture the structural aspects over which SIDS and other island territories have no control, and thus are independent of political orientations. A Principal Component Analysis (PCA) was used to select uncorrelated variables and thus avoids collinearity. We then used a multi-layer Data Envelopment Analysis (MLDEA) model to aggregate the sub-indexes. Compared to the standard DEA model, MLDEA highly improved the discriminating power of the model following weight restrictions incorporated to the different layers of the hierarchical structure. MLDEA is thus useful when indicators can be grouped into the same categories (for instance indicators falling under the economic dimension).Our contribution is thus twofold:conceptual by proposing a new framework to define energy vulnerability, and methodological by using a combination of PCA and MLDEA that are data-driven to construct our composite index. Although no composite index can eliminate subjectivity.

Quantitatively measuring energy vulnerability has several purposes: comparing SIDS and other island territories (net oil importers and net oil exporters), identifying priority areas (energy issues that require immediate attention), and acting as a decision-making tool for policy makers to address and reduce energy vulnerability.Assessing vulnerability is of utmost importance since it could be detrimental to the sustainable energy future as well as the economic prosperity and development of these territories in the long-run. It should be noted however that islands obtaining an optimal score of one for the energy vulnerability index can still be vulnerable to external shocks.

By means of country clustering, we grouped SIDS and other island territories into clusters according to similar energy practices. Overall, we showed that instead of analysing solely inter-region disparities, country clustering helped to gain better insight into the different dimensions contributing to energy vulnerability. We identified for each cluster the strengths and weaknesses and gave policy recommendations for each group. This can ultimately result in the erection appropriate inter- and intra-regional networks to share best practices and support cooperation in these regions.Reunion and Tuvalu were the least vulnerable islands since they scored the optimal score of one under the MLDEA. On the other hand, the Federated States of Micronesia ranked last since it was the most vulnerable from an energy viewpoint. Reunion and Tuvalu can thus both serve as benchmarks for Micronesia and other underperforming SIDS, especially in terms of energy mix diversity and energy efficiency in the transport sector.

Following results obtained, we recommend that SIDS and other island territories work on their adaptive capacity that results from political orientations and policies in order to mitigate both the exposure and shock components of energy vulnerability. There exist uncertainties around increases in energy demand, fuel availability and prices, technology changes as well as environmental impacts of energy consumption. Therefore, diversifying the domestic energy mix arises as a key strategy to reduce dependency on imported fossil fuels by integrating more renewable energy into the mix. Consequently, SIDS and other island territories will be less vulnerable to price fluctuations of fossil fuels and supply disruptions. Moreover, they will be able to reduce their carbon footprint by limiting CO2 emissions from energy use and lower their energy bills. Thus, more resources (financial and human) can be devoted to poverty reduction for instance. However, SIDS and other island territories would still have to face intermittency issues of certain types of renewable energy such as solar and wind, as well as high upfront costs for new technologies.

Future research developments could include the study of all developing countries in order to expand knowledge about this complex and multidimensional phenomenon. A hypothetical country with complete energy security could be used to measure the additional effort each country has to provide to mitigate vulnerability. It would be useful to determine critical thresholds under which a country is considered vulnerable since absolute security is almost impossible to achieve considering energy sector's uncertainties. Valuable insights can also be gained by monitoring a small group of countries over time to better capture the evolution of energy vulnerability to better assess a specific country's effort in achieving its energy transition. It is crucial that cooperation takes place not only within ACP regions but should also be encouraged through inter-regional technology transfers based on clusters identified earlier. We believe that inter- and intra-regional cooperation may ultimately provide more tailored solutions to the needs of small island economies.

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Appendix A

Table A.1 Basic indicators for SIDS and other island territories in 2015

Country	Code	Population density (pop/km^2)	GDP/cap ($ PPP)	NOE/ NOI
Atlantic, Indian Ocean and South China Sea (AIMS)				
Singapore	SGP	7806.77	81741.10	NOI
Bahrain	BHR	1779.32	43926.47	NOE
Seychelles	SYC	203.08	24856.56	NOI
Mauritius	MUS	621.97	18864.11	NOI
Reunion	REU*	337.32	17736.69	NOI
Maldives	MDV	1394.68	13705.01	NOI
Cape Verde	CPV	132.24	5915.12	NOI
Sao Tomé and Principe	STP	203.70	2947.51	NOI
Guinea-Bissau	GNB	62.96	1446.49	NOI
Comoros	COM	417.75	1413.06	NOI
Madagascar	MDG*	41.65	1377.17	NOI
Caribbean				
Trinidad and Tobago	TTO	265.13	31524.59	NOE
Bahamas	BHS	38.65	28407.13	NOI
Saint Kitts and Nevis	KNA	208.80	24169.86	NOI
Antigua and Barbuda	ATG	227.10	20154.95	NOI
Barbados	BRB	638.68	16458.10	NOI
Suriname	SUR	3.55	14766.80	NOE
Dominican Republic	DOM	217.93	13395.92	NOI
Grenada	GRD	314.19	12757.97	NOI
Saint Lucia	LCA	290.50	12522.04	NOI
Saint Vincent and the Grenadines	VCT	280.65	10468.26	NOI
Dominica	DMA	97.55	9941.89	NOI
Belize	BLZ	15.75	8127.66	NOI
Jamaica	JAM	265.18	8095.26	NOI
Guyana	GUY	3.90	7076.94	NOI
Cuba	CUB	110.18	6444.97	NOI
Haiti	HTI	118.32	1651.23	NOI
Pacific				
Palau	PLW	46.28	14028.68	NOI
Fiji	FJI	48.83	8477.64	NOI
Timor-Leste	TLS	83.46	7398.84	NOE
Samoa	WSM	68.47	5558.79	NOI
Tonga	TON	147.73	5189.84	NOI
Papua New Guinea	PNG	17.49	3824.73	NOE
Tuvalu	TUV	366.70	3419.20	NOI
Micronesia (Federated States of)	FSM	151.19	3271.27	NOI
Vanuatu	VUT	21.71	2806.79	NOI
Solomon Islands	SLB	22.34	2149.22	NOI
Kiribati	KIR	138.77	1967.30	NOI

Note: Reunion and Madagascar are not SIDS UN-members but are in the AIMS region
NOI = net oil importer, NOE = net oil exporter

Appendix B

Table B.1 Initial set of 21 variables and data sources

Dimension	**Code**	**Name**	**(E) or (S)**	**Data source**
Social	SOC1	Share of population with access to electricity	E	World Bank (SE4ALL)[8]; UN statistics (SDGs)[9]
	SOC2	Share of population with access to clean fuels and technologies	E	
	SOC3	Remoteness	E	UNCDP (LCD data)
Economic	ECO1	Primary energy supply per capita	S**	UN Energy Balances (2015); Gross Value Added is obtained from the UN Statistics Division (National Accounts Estimates of Main Aggregates)[10]
	ECO2	Total final energy consumption per capita	S	
	ECO4	Primary energy supply per unit of GDP	S**	
	ECO5	Total final energy consumption per unit of GDP	S	
	ECO7	Energy intensity of the agricultural sector	S	
	ECO8	Energy intensity of the service/commercial sector	S	
	ECO9	Energy intensity of the manufacturing sector	S	
	ECO10	Energy intensity of the transport sector	S	
	ECO11	Renewable energy as a share of TFEC	E	World Bank (SE4ALL); UN statistics (SDGs)
	ECO12	Renewable energy as a share of total electricity	E	
	ECO13	Energy import dependency	E	UN Energy Balances (2015) [11]
	ECO14	Energy mix diversity	E**	
	ECO15	Energy bill	S	
	ECO16	Overall system conversion efficiency	E	
	ECO17	Overall self-sufficiency	E	
Environmental	ENV1	CO_2 emissions per capita	S	EDGAR (Emissions Database for Global Atmospheric Research)
	ENV2	CO_2 emissions per unit of GDP	S	
	ENV3	CO^2 content of TPES	S	EDGAR; UN Energy Balances (2015)

8 https://datacatalog.worldbank.org/dataset/sustainable-energy-all (accessed on 18/03/2019)

9 https://unstats.un.org/sdgs/indicators/database (accessed on 18/03/2019)

10 https://unstats.un.org/unsd/snaama/downloads (accessed on 18/03/2019)

11 https://read.un-ilibrary.org/natural-resources-water-and-energy/2015-energy-balances_5869b981-en#page1 (accessed on 18/03/2019)

Note: TES = Total Energy Supply; TFC = Total Final Consumption; E = Exposure; S = Shock
*Based on classification made by d'Artigues and Vignolo. Remaining indicators were categorized by authors.

Appendix C

We decided to conduct a PCA to reduce dimensionalityin our multivariate data set. Information is extracted to form a new set of variables called principal components, denoted as follows:

$$\min\,(n-1, p)$$

Where n is the number of observations and p the number of variables.The orthogonal transformation ensures that the first principal component accounts for the largest variance possible (see table below). PCA was thus computed using the *FactoMineR* and *factoextra* packages in R. Results of the PCA (Table C.1) suggest that seven dimensions need to be kept in order to explain the phenomenon without losing substantial information. Indeed, dimensions with eigenvalues higher than or equal to one can be kept. However, we decided to keep only three dimensions following a scree plot analysis (Fig. C.1).

Table C.1 Eigenvalues and variances

	Eigenvalue	Variance (%)	Cumulativevariance (%)
Dim.1	5.635	26.833	26.83368
Dim.2	3.965	18.883	45.7169
Dim.3	2.096	9.981	55.69888
Dim.4	1.858	8.850	64.54933
Dim.5	1.513	7.207	71.75724
Dim.6	1.155	5.503	77.26124
Dim.7	1.059	5.047	82.30845
Dim.8	0.959	4.568	86.87658
Dim.9	0.711	3.387	90.26401
Dim.10	0.582	2.771	93.03591
Dim.11	0.465	2.218	95.25427
Dim.12	0.434	2.071	97.32551
Dim.13	0.237	1.131	98.45664
Dim.14	0.130	0.623	99.07984
Dim.15	0.073	0.348	99.42836
Dim.16	0.042	0.203	99.63181
Dim.17	0.040	0.192	99.82425
Dim.18	0.019	0.090	99.91522
Dim.19	0.010	0.051	99.9668
Dim.20	0.005	0.024	99.99104
Dim.21	0.001	0.008	100

Note: Dim.1-Dim.21 represent linear combinations of the 21 initial variables. Each linear combination differs in terms of individual indicator contribution to each dimension. See Fig. C.2 for graphical visualization.

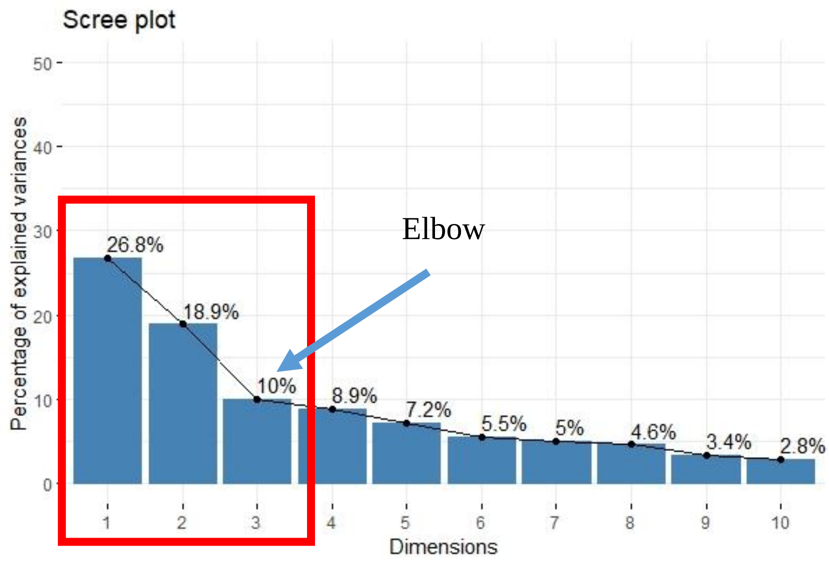
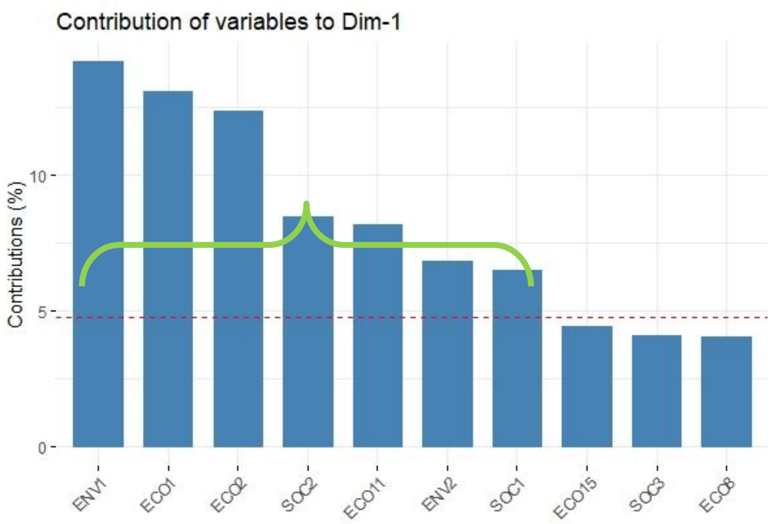
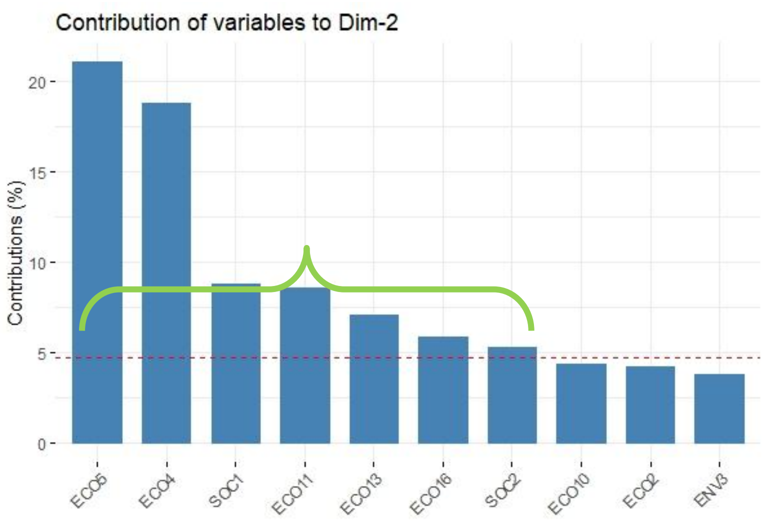


Fig. C.1 Scree plot analysis (% of variance explained)
Source: authors





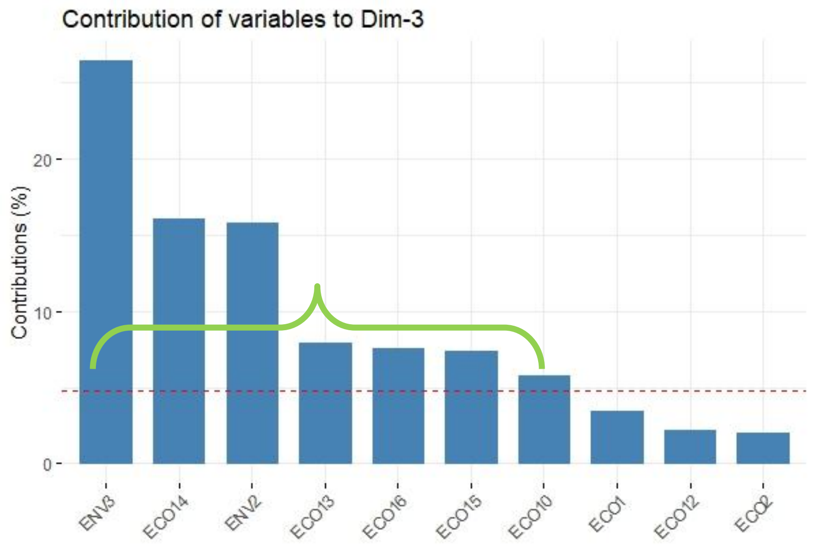


Fig. C.2 Contribution of variables to the three principal components (dimensions)
Source: authors

Table C.2 Correlation matrix of final set of selected indicators

	ECO1	SOC1	ECO5	ECO13	ECO16	ENV3	ECO14	ECO10
ECO1	1							
SOC1	-0.29	1						
ECO5	0.5	0.33	1					
ECO13	0.14	-0.35	-0.35	1				
ECO16	-0.32	0.48	0.38	-0.29	1			
ENV3	-0.08	-0.35	-0.34	0.06	0.04	1		
ECO14	-0.1	0.19	-0.04	0	0.06	-0.4	1	
ECO10	0.11	0.09	0.48	-0.17	0.34	0	-0.29	1

Source: authors

Appendix D

Table D.1 Normalized data on the selected eight indicators

Country	SOC1	ECO1	ECO5	ECO10	ECO13	ECO14	ECO16	ENV3
ATG	0.963	0.879	0.852	0.669	0.799	0.000	0.372	0.638
BHS	1.000	0.864	0.858	0.904	0.840	0.010	0.664	0.090
BHR	1.000	0.300	0.709	0.741	0.887	0.319	0.000	0.743
BRB	1.000	0.909	0.854	0.873	0.797	0.044	0.489	0.367
BLZ	0.905	0.941	0.714	0.628	0.923	0.878	0.798	0.496
CPV	0.887	0.983	0.881	0.841	0.798	0.553	0.620	0.968
COM	0.714	1.000	0.791	0.952	0.944	0.630	0.499	0.898
CUB	1.000	0.940	0.765	0.964	0.912	0.574	0.209	0.585
DMA	0.999	0.949	0.882	0.840	0.864	0.243	0.232	0.539
DOM	0.983	0.958	0.917	0.862	0.857	0.847	0.496	0.531
FJI	0.967	0.939	0.793	0.762	0.868	0.551	0.395	0.738
GRD	0.905	0.947	0.878	0.821	0.868	0.252	0.547	0.038
GNB	0.000	0.982	0.187	0.668	1.000	0.400	0.000	0.975
GUY	0.809	0.935	0.661	0.693	0.887	0.468	0.673	0.357
HTI	0.282	0.983	0.450	0.782	0.991	0.495	0.638	0.924
JAM	0.968	0.947	0.782	0.750	0.838	0.406	0.561	0.444
KIR	0.890	0.998	0.827	0.781	0.858	0.179	0.526	0.628
MDG	0.058	0.998	0.733	0.828	0.983	0.727	0.607	0.929
MDV	1.000	0.935	0.825	0.709	0.824	0.055	0.829	0.595
MUS	0.985	0.922	0.917	0.823	0.832	0.938	0.266	0.692
FSM	0.635	0.975	0.588	0.000	0.854	0.069	0.660	0.554
PLW	0.990	0.763	0.436	0.170	0.819	0.000	0.613	0.959
PNG	0.095	0.977	0.743	0.743	0.938	0.193	0.593	0.651
REU	1.000	0.893	0.829	0.882	0.871	1.000	0.517	0.914
KNA	0.999	0.907	0.930	0.866	0.846	0.055	0.234	0.605
LCA	0.967	0.953	0.905	0.871	0.850	0.071	0.414	0.307
VCT	0.994	0.959	0.874	0.779	0.863	0.204	0.596	0.254
WSM	0.999	0.962	0.731	0.682	0.884	0.599	0.663	0.840
STP	0.587	0.988	0.778	0.849	0.894	0.652	0.585	0.899
SYC	0.996	0.897	0.897	0.894	0.608	0.057	0.493	0.449
SGP	1.000	0.635	0.919	0.965	0.000	0.723	0.276	0.765
SLB	0.478	0.994	0.725	0.820	0.940	0.639	0.836	0.657
SUR	0.661	0.921	0.818	0.696	0.892	0.524	0.727	0.505
TLS	0.620	1.000	1.000	0.836	0.872	0.318	0.339	0.606
TON	0.956	0.984	0.857	0.599	0.835	0.100	0.699	0.000
TTO	1.000	0.000	0.000	0.647	0.994	0.268	0.536	0.710
TUV	0.989	0.989	0.860	1.000	0.864	0.178	0.349	1.000
VUT	0.357	0.993	0.780	0.788	0.884	0.638	0.878	0.716

Appendix E Sensitivity analysis

We assess the robustness of our MLDEA model by comparing country ranking for sensitivity analysis purposes. This is achieved by using another aggregating technique that is commonly used by researchers: PCA. Note that PCA mentioned earlier in the text was used to select linearly uncorrelated variables. Here, we build on that analysis to aggregate those variables.We choose to retain three principal components (dimensions). Sub-indicator weights correspond to the contribution of each sub-indicator to a selected dimension. The composite index is then expressed as a weighted average of the three dimensions with eigenvalues acting as weighting coefficients for each dimension.

Table E.1: Contribution of indicators to the three dimensions

Indicators	**Code**	**Dim1**	**Dim2**	**Dim3**
Share of population with access to electricity	SOC1	6.482	8.836	0.002
TES/capita	ECO1	13.058	3.018	3.455
TFC/GDP	ECO5	1.230	21.087	0.022
Energy intensity of the transport sector	ECO10	0.477	4.386	5.808
Energy import dependency	ECO13	1.424	7.077	7.943
Energy mix diversity	ECO14	2.565	0.434	16.054
Overall system conversion efficiency	ECO16	3.052	5.907	7.555
CO_2 content of TPES	ENV3	1.401	3.812	26.461

Dim1 $= f(\text{ECO1})$
$= 0.06482*\text{ECO1}$ Eq. (E.1)

Dim2 $= f(\text{SOC1, ECO5})$
$= 0.08836*\text{SOC1} + 0.21087*\text{ECO5}$ Eq. (E.2)

Dim3 $= f(\text{ECO10, ECO13, ECO14, ECO16, ENV3})$
$= 0.05808*\text{ECO10} + 0.07943*\text{ECO13} + 0.16054*\text{ECO14} + 0.07555*\text{ECO16} + 0.26461*\text{ENV3}$ Eq. (E.3)

EnVI $= 5.635*\text{Dim1} + 3.965*\text{Dim2} + 2.096*\text{Dim3}$ Eq. (E.4)

Table E.2: Shift in country ranking under PCA and MLDEA

	PCA		**MLDEA**		**Shift in ranking**
Country	Score	**Rank**	Score	**Rank**	**PCA-MLDEA**
REU	2.547	**1**	1	**1**	**0**
TUV	2.362	**5**	1	**1**	**4**
CPV	2.462	**2**	0.991	**3**	**-1**
WSM	2.315	**7**	0.97	**4**	**3**
COM	2.339	**6**	0.958	**5**	**1**
MUS	2.429	**3**	0.948	**6**	**-3**
DOM	2.367	**4**	0.94	**7**	**3**
BLZ	2.185	**10**	0.934	**8**	**2**
MDV	2.085	**20**	0.922	**9**	**11**

STP	2.279	**8**	0.921	**10**	**-2**
FJI	2.239	**9**	0.919	**11**	**-2**
CUB	2.153	**13**	0.918	**12**	**1**
SGP	2.179	**11**	0.909	**13**	**-2**
PLW	1.776	**34**	0.906	**14**	**20**
KNA	2.096	**19**	0.894	**15**	**4**
DMA	2.098	**17**	0.888	**16**	**1**
KIR	2.097	**18**	0.878	**17**	**1**
SLB	2.105	**16**	0.877	**18**	**-2**
JAM	2.041	**22**	0.877	**19**	**3**
VUT	2.134	**14**	0.873	**20**	**-6**
VCT	1.972	**25**	0.863	**21**	**4**
SYC	1.983	**24**	0.863	**22**	**2**
BRB	1.931	**27**	0.86	**23**	**4**
ATG	1.998	**23**	0.857	**24**	**-1**
HTI	1.874	**28**	0.851	**25**	**3**
LCA	1.951	**26**	0.848	**26**	**0**
BHR	1.809	**31**	0.842	**27**	**4**
GNB	1.438	**37**	0.839	**28**	**9**
SUR	2.057	**21**	0.835	**29**	**-8**
TLS	2.162	**12**	0.834	**30**	**-18**
MDG	2.118	**15**	0.834	**31**	**-16**
BHS	1.792	**32**	0.826	**32**	**0**
GUY	1.872	**29**	0.816	**33**	**-4**
TTO	1.164	**38**	0.807	**34**	**4**
GRD	1.834	**30**	0.789	**35**	**-5**
TON	1.767	**35**	0.787	**36**	**-1**
PNG	1.778	**33**	0.714	**37**	**-4**
FSM	1.648	**36**	0.705	**38**	**-2**

Note: A negative sign for shift in rankings indicates a loss in ranks.

Table E.3: Correlation matrix for country rankings under MLDEA and PCA

	MLDEA	PCA
MLDEA	1	
PCA	0.83	1

We tested the degree of similarity in country rankings under PCA and MLDEA. Thecorrelation matrix in Table E.3 suggests that country rankings under both methods are globally highly correlated with a Spearman rank correlation coefficient$\rho$of 0.83. It lies in the [-1,1] interval with -1 indicating that rankings are opposite to each other and 1 indicating perfect agreement between the two.

We assess the robustness of the model scores by calculating the average shift in country rankingsas follows:

$$\overline{R_s} = \frac{1}{N}\sum_{c=1}^{M} |Rank_{ref}(CI_c) - Rank(CI_c) \qquad \text{Eq. (E.1)}$$

Where $\overline{R_s}$ is the average shift in country rankings, $Rank_{ref}(CI_c)$ is the rank of country c under MLDEA and $Rank(CI_c)$ is the rank of country c under PCA and N the number of observations (countries) in the data set.

Table E.4: Average shifts in country rankings

	PCA
$\overline{R_s}$	4.2

Table E.4 suggests that on average, the absolute shift in country rankings from MLDEA to PCA is of 4.2 ranks, with a standard deviation (σ) of 4.7. We argue that shifts in country rankings do not seem to challenge the robustness of our composite index under MLDEA considering outliers are present in the data set (MDG, MDV, PLW and TLS). Overall, results are not fundamentally changed.