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An assessment of energy vulnerability in Small Island Developing States

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ABSTRACT

Small Island Developing States (SIDS) suffer from several structural characteristics that jeopardize their ability to achieve a sustainable energy future. Their reliance on imported fossil fuels exacerbates their exposure to external threats on international energy markets. Their energy systems are also exposed to internal disturbances that disrupt the proper production, transmission and distribution of energy. The aim of this paper is to investigate the extent to which island energy systems are vulnerable to shocks and internal dysfunctions over which they have no control. For this purpose, we build a composite index of energy vulnerability using the Multi-Layer Benefit-of-the-Doubt approach. Such an approach enables the identification of economic, environmental and social dimensions that play an important role in the relative energy vulnerability of SIDS. Ultimately, we shed light on the priority areas requiring immediate attention in order to mitigate energy vulnerability in SIDS.

Keywords: Energy vulnerability, SIDS, composite index, energy security, Multi-Layer Benefit-of-the-Doubt Model

Declarations of interest: none

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1. INTRODUCTION

An ongoing challenge for countries worldwide is to ensure the uninterrupted supply of energy to secure energy services for their populations (Sovacool, 2013). Energy plays a vital role in economic growth and development as it is a significant input for the proper functioning of economic and social activities. Conversely, 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. Governments worldwide put this strategic good on the front burner (Patlizianas *et al.*, 2008; Böhringer and Bortolamedi, 2015) calling for sound management and planning.

Small island developing states face multiple threats. Energy challenges are even greater in these territories that are already afflicted by several structural handicaps such as small size, remoteness, and non-interconnected electrical networks. This puts strain on their economic prosperity (Briguglio, 1995; Adrianto and Matsuda, 2004; Garabedian and Hoarau, 2011; Blancard and Hoarau, 2013) as well as their ability to ensure a sustainable energy future. Indeed, most SIDS are not endowed with fossil energy resources. Their extensive reliance on imported fossil fuels appear as one of the most challenging issues they must face. This situation tends to exacerbate their exposure 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.

Energy vulnerability concerns are not new. This is confirmed by the substantial amount of literature dedicated to the study of this phenomenon, along with other concepts such as energy security. In this perspective, energy security is seen as the 'low vulnerability of vital energy systems' (Guivarch and Monjon, 2017, p. 530). Recurring energy security dimensions include 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). To assess energy vulnerability and security, several methods can be used[2]. Among these, we find composite indices that have become increasingly popular due to their simplicity and transparency, and above all their ability to capture the complexity and multidimensionality of phenomena such as energy vulnerability.

Most studies focus on energy (in)security (Jansen *et al.*, 2004; Scheepers *et al.*, 2007; Sovacool and Mukherjee, 2011)[3]. Research on macroeconomic energy vulnerability is relatively scarce in the literature. We have identified several conceptual and methodological shortcomings in existing literature: on a conceptual note, no suitable framework has been proposed to capture energy vulnerability of energy systems. Some studies only consider specific aspects of energy vulnerability. Gupta (2008) assessed the oil vulnerability of several oil importing countries. A recent study by Ioannidis *et al.* (2019) investigated island energy vulnerability through energy supply security. Although insightful, the study fails to capture the more global scope of this phenomenon in island energy systems. On methodological grounds, some studies transform indicators using popular normalization techniques prior to the aggregation step (Gupta, 2008; Gnansounou; 2008). Studies previously mentioned do not consider the nested structure of composite indices with multiple

[2] See Mansson et *al.* (2014) for a review of commonly used methodologies to assess energy security.
[3] See Valdés (2018) for a review focused on energy security indicators.

dimensions. Finally, based on country coverage, existing studies mostly focus on industrialized nations or emerging economies (Gnansounou, 2008; Sovacool, 2013; d'Artigues and Vignolo, 2012) while small island developing states are less studied (Genave, 2019).

This study thus has three contributions. The first one is conceptual. No proper framework has been established so far in the literature for the study of macroeconomic vulnerability. Moreover, no consensus has been reached so far on a single best definition of the latter. Energy vulnerability is a major challenge that negatively affects the economic, environmental, and social prospects of countries worldwide, including SIDS. We believe that providing a suitable framework for the study of such phenomenon is an important first step towards mitigating energy vulnerability. We propose a definition broad enough that allows for the identification of various factors that directly or indirectly contribute to energy vulnerability based on the structural economic vulnerability literature (see Guillaumont, 2009, 2010) which makes use of shock and exposure components. This ad hoc structure fits well with energy vulnerability studies since the objective is to stress on those factors over which SIDS have no control and are therefore independent of current political orientations. Energy vulnerability is thus defined as the 'degree of sensitivity of an energy system to external threats or internal dysfunctions related to technology availability for the production, transmission and distribution of energy'. The exposure component essentially captures the extent to which these territories are sensitive to potential adverse events. The shock component accounts for the possible transformations these territories will undergo following a specific shock. We then select a pool of indicators, categorized as economic, environmental or social dimensions, that are linked to one another to form a multi-layer hierarchical structure for our composite index of energy vulnerability.

Secondly, from a methodological viewpoint, the indicators reflecting these two sub-indices (exposure and shock) and entering thereafter in the composite index construction are selected by means of a Principal Component Analysis (PCA). After this identification step, the selection of the weighting system and the aggregation method are generally the next steps for constructing a composite index. As a methodological contribution of our paper, we then implement the Färe *et al.* (2019) model combined with a Multi-Layer Benefit-of-the-Doubt (MLBoD) initially proposed by Shen *et al.* (2013). On the one hand, the approach of Färe *et al.* (2019) deals with desirable and reverse indicators, i.e. indicators having a positive and a negative impact respectively on the composite index. On the other hand, the MLBoD model reflects the hierarchical structure of the composite index, taking into account the contribution of sub-indices and the different dimensions to energy vulnerability. To the best of our knowledge, no other existing studies on energy vulnerability have combined such approaches so far.

Finally, we apply our composite index of energy vulnerability to energy systems in 38 SIDS UN-members recognised by the United Nations. We argue that past and current research failed to give sufficient consideration to SIDS when it comes to constructing a meaningful composite index to capture energy vulnerability. This paper therefore aims to fill the gap in existing literature on the subject with the objective to better understand the critical energy challenges faced by these territories. Existing studies on energy vulnerability and security do not incorporate the specificities of small island developing states. We hope to overcome the lack of a synthetic index capturing energy vulnerability taking into account the underlying economic, environmental and social dimensions of energy vulnerability (IAEA, 2005).

The remainder of this paper is organized as follows: Section 2 provides insights as regards the link between island energy systems and vulnerability. Section 3 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. Results are presented and discussed in section 4. Section 5 concludes and provides the way forward.

2. HETEROGENEOUS ISLAND ENERGY SYSTEMS AND VULNERABILITY

Encontre (2004) identifies several lists of small island developing states ranging from 29 to 48[4] territories. The United Nations (UN) recognizes 58 SIDS[5], of which 38 are UN members. We opted for the list of SIDS UN-members to investigate the relative energy performances of island energy systems[6]. The ongoing energy challenges faced by SIDS cover several dimensions including economic, environmental and social aspects.

On the economic front, challenges include heavy reliance on imported fossil fuels such as coal, petroleum products mainly for electricity generation and fuel for the transport sector (Blechinger *et al.*, 2016; Atteridge and Savvidou, 2019). Indeed, 31 out of the 36 SIDS are considered net energy importers (see appendix A) based upon their respective energy balances[7]. There is strong heterogeneity amongst net energy importers. Of the 31, 24 SIDS had energy dependency rates are above 80% in 2015. On the other hand, two SIDS had dependency rates lower than 30% in the same year mainly due to the use of conventional sources of energy such as fuel wood, biomass and waste[8]. The paradox is that a majority of small island states have substantial indigenous renewable sources like solar and wind energy that are still untapped (Blechinger *et al.*, 2016). This is mainly due to poor energy infrastructures and high initial upfront costs of greener technology alternatives (Gils and Simon, 2017).

Reliance upon external sources of energy further exacerbates their exposure to external threats on international energy markets such as energy price fluctuations (mainly those of petroleum products) that could potentially be disruptive to their domestic economies (Hamilton, 2008). Moreover, higher energy prices further burden their national budgets, thus affecting their balance of payments (Hamilton, 2003; Henriques and Sadorsky, 2011). The concentration of fossil fuel reserves in a few countries implies energy security concerns for net importing countries, including SIDS. Political instability in these producing regions can lead to energy access issues and consequently disruption risks in their primary energy supply chains (Ioannidis *et al.*, 2019).

Highly concentrated energy mixes could be detrimental to the proper functioning of their economies. A significant proportion of islands' primary energy supply is sourced from fossil fuels. Energy mix concentration can also arise when a few indigenous sources of energy dominate the domestic mix. Some least developed SIDS make substantial use of bio-fuels and waste, which account for over 70%

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[4] A pragmatic list of 29 SIDS of the United Nations Conference on Trade and Development (UNCTAD), a political list of 39 SIDS which altogether form the Alliance of Small Island States, an institutional list of 46 SIDS according to the United Nations, and an economic list of 48 SIDS according to the United Nations Secretariat.

[5] United Nations Office of the High Representative for the Least Developed Countries, Landlocked Developing Countries, and Small Island Developing States (UN-OHRLLS) (http://unohrlls.org/about-sids/), accessed on 07/10/2019

[6] 36 SIDS were selected instead since data were not available for Marshall Islands and Nauru.

[7] From The 2015 Energy Balances published by the United Nations Statistics Division (https://unstats.un.org/unsd/energystats/pubs/balance/, accessed on 15/10/2019)

[8] These include SIDS such as Guinea-Bissau and Haiti (from the Sustainable Energy For All (SE4ALL) data base of The World Bank (https://datacatalog.worldbank.org/dataset/sustainable-energy-all, accessed on 15/10/2019)

of their primary energy supply[9]. On the other hand, SIDS endowed with natural fossil resources are also exposed to supply disruption risks that could negatively affect the production, transmission and distribution of energy. A well-diversified energy mix is thus seen as a bulwark against external shocks (Percebois, 2007; Gupta, 2008; Gnansounou, 2008, d'Artigues and Vignolo, 2012).

Social challenges include accessibility and affordability related to energy use. The gap between advanced economies and developing countries translates into the use of modern energy services for several uses versus the use of traditional fuels such as charcoal and fuelwood for cooking, heating and lighting (IAEA, 2005; Vera and Langlois, 2007). As of 2015, several SIDS struggled to provide universal access to electricity to its population. This is a severe problem encountered by less developed SIDS with the lowest access rates ranging from 15 to 84% as regards access to electricity and 1.5% to 18% as regards access to clean technologies in 2015[10]. This problem is also extended to the provision of modern and clean technologies for lighting and cooking, which spurs health-related concerns in these territories due to the combustion of traditional fuels that causes indoor air pollution.

Emissions of greenhouse gases are linked to the production, transmission and distribution of energy which have long-term impacts on the environment. Environmental degradation due to the production of energy and its use by end users put strain on the sustainable development of SIDS (Vera and Langlois, 2007). Environmental concerns have gained increasing attention worldwide, with renowned publications like Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report warning against the disruptive impacts of climate change and global warming on economies, societies and the environment as a whole (IPCC, 2014). On average carbon emissions have rose 94% between 1970 and 2015 to reach 3.85 tons per capita[11]. Although contributing to a non-significant part to global warming (Heger *et al.*, 2008; Julca and Paddison, 2010), SIDS have pledged through Nationally Determined Contributions following the Paris Agreement[12] to abate CO_2 emissions amongst other things.

SIDS share common characteristics and face similar energy challenges. However, they form a rather heterogeneous group, hence, the importance of assessing energy vulnerability in these territories. The following section describes the methods used to measure this phenomenon.

3. METHODOLOGY

In this paper, we assess the energy vulnerability in small island developing states based on several energy indicators. For this purpose, we adopt a data-driven approach consisting of several steps from indicator selection to aggregation in view of computing a composite index of energy vulnerability.

3.1. Data set description

3.1.1 Data

The energy vulnerability index was computed for 36 SIDS for the year 2015. These territories are grouped into three main regions: AIMS, Caribbean and the Pacific. Initially, we intended to use the

[9] The 2015 Energy Balances published by the United Nations Statistics Division (https://unstats.un.org/unsd/energystats/pubs/balance/, accessed on 11/11/2019)

[10] World Development Indicators, The World Bank (http://datatopics.worldbank.org/world-development-indicators/, accessed on 14/11/2019)

[11] Emissions Database on Global Atmospheric Research, Joint Research Council of the European Commission (https://edgar.jrc.ec.europa.eu/, accessed on 14/11/2019)

[12] NDC registry (https://www4.unfccc.int/sites/NDCStaging/Pages/All.aspx, accessed on 15/11/2019)

complete list of SIDS UN-members[13] 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. Data were retrieved from the United Nations Statistics Division and The World Bank. Data on CO_2 emissions were extracted from the Emission Database for Global Atmospheric Research [14](EDGAR; Olivier *et al.*, 2016). All indicator data sources are reported in appendix B.

3.1.2 Selection of indicators

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)[15] proposed by the International Atomic Energy Agency (IAEA, 2005) and existing literature on energy security and vulnerability (Gnansounou, 2008; Gupta, 2008; Iddrisu and Bhattacharyya, 2015; Narula and Reddy, 2016; Genave, 2019).

As regards indicator selection, there is no best practice approach. Principal Component Analysis (PCA) is then used to compute a covariance matrix in order to reduce redundancy in the data set. The principal components are given by the linear combination of all indicators. The first principal component always accounts for the greatest variance. This procedure is detailed in Appendix C. 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 that explain more than 60% of the variance in the dataset. The rationale for each selected indicator used in the construction of our composite index is provided in Table 1.

[Insert Table 1 here]

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 comprises four dimensions (two under the exposure sub-index - economic and social - and two under the shock sub-index - economic and environmental). The third layer is composed of two sub-components (exposure sub-index and shock sub-index). The fourth and final layer (EnVI) is obtained by aggregating the two sub-components. However, it should be noted that the composite index should be interpreted as an index of non-vulnerability since the MLBoD approach computes efficiency scores (i.e. the higher the better). Raw data on the eight selected indicators are provided in appendix D.

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[13] We opted for the list of SIDS of the United Nations Office of the High Representative for the Least Developed Countries, Landlocked Developing Countries, and Small Island Developing States (UN-OHRLLS). This list recognizes a total of 58 SIDS, of which 38 are UN-members. We selected 36 SIDS and two other island territories in our paper since not enough data were available for Marshall Islands and Nauru (http://unohrlls.org/about-sids/, accessed on 07/10/2019).

[14]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).

[15] 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).

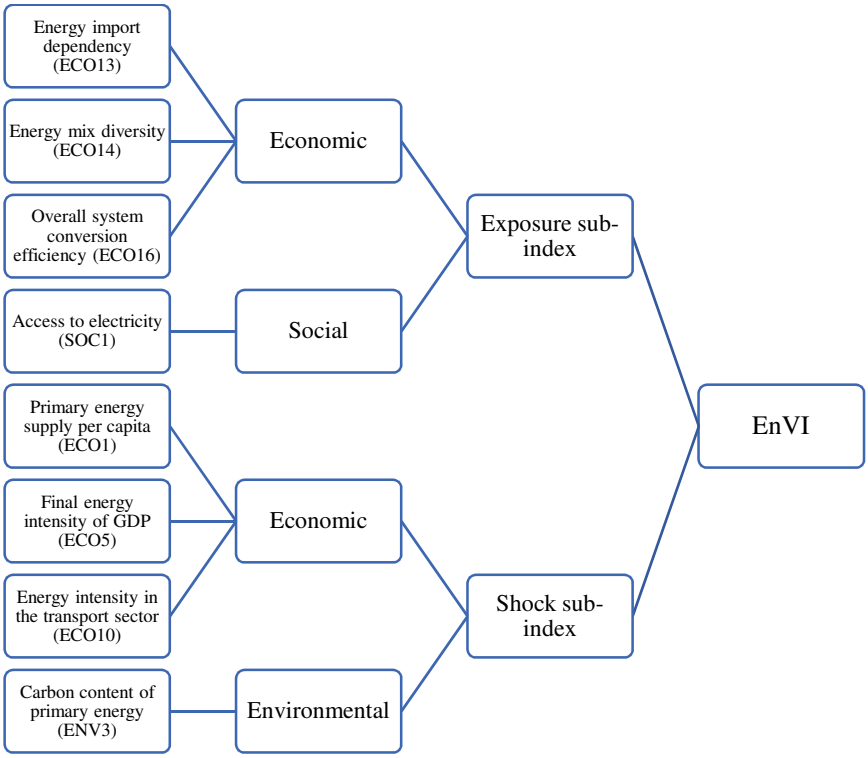

Fig. 1 Hierarchical structure of the composite index of energy vulnerability (EnVI)
Source: authors
[To be printed in colour]

The next step is to assign weights to all energy vulnerability indicators and aggregate them into a unique value.

3.2 Composite indicator construction

Energy vulnerability is thus expressed as the weighted average of all vulnerability dimensions for a selected country in terms of each indicator. Our challenge lies in the determination of meaningful weights required to construct the composite index. Weighting methods are broadly categorized into statistical models (e.g. principal components or regression analysis) and those based upon public/expert opinion (e.g. budget allocation process or conjoint analysis). In the former category, we also find the Benefit-of-the-Doubt (BoD) model which is rooted in Data Envelopment Analysis (DEA) initially proposed by Charnes *et al.* (1978).

DEA and related models present numerous advantages in that sense where it is solely based on data and thus avoids subjectivity associated with techniques relying on expert judgement or public opinion polls. This is particularly useful when dealing with composite indices generally characterized by uncertainty and lack of consensus on an appropriate weighting scheme. DEA selects weights that maximize the composite index for each country under investigation (Zhou *et al.*, 2007). Each country is allowed to use the set of weights which places him in the best possible position. Therefore, countries are less likely to contest assigned weights (Cherchye *et al.*, 2007).

Two remarks can be made about DEA methodology. First, the score obtained by a country reflects relative energy vulnerability compared to the rest of the sample. Therefore, a country with a score equal to unity may be vulnerable in absolute terms. In order to take into account this second element, we can imagine other vulnerability measures based on samples integrating other countries or groups

less vulnerable in absolute terms. The real position of countries under investigation can be thus analysed on a different scale.

Second, despite numerous advantages, it should be noted that DEA methodology is deterministic in nature, causing scores to be sensitive to the noise problem in the data (e.g. presence of outliers). Therefore, additional developments may be necessary to solve this problem to avoid robust results being negatively affected[16]. Among them, we find a simple and relevant subsampling approach inspired by Kneip *et al*. (2008)[17]. As presented by Valdmanis *et al*. (2017) and Leleu *et al*. (2018) in intuitive manner, the technique is implemented as follows. First, a large number of subsamples, of a predetermined size, are selected from the initial sample of observed decision-making units (countries in this case). Second, the estimated composite index (CI) is computed for each sample, and the final estimate is simply the average across the sub-samples. Since the estimated frontier is based on a random selection of countries varies over the sub-samples, a country is not always compared with potential outliers. Thus, final result can be interpreted as a robust measure of CI. Moreover, once the distribution of CI scores is obtained for each entity, we derive a confidence interval (see appendix E) for our composite indicator by eliminating α/2 of the value at each tail of the distribution (hereafter, we will consider a significance level α of 5%).

3.2.1 The Benefit-of-the-Doubt (BOD) model

In the field of composite indicators, the multiplicative form of the output-oriented basic DEA model with multiple outputs (i.e. indicators) and a single dummy input equal to unity have been used to determine the weighting scheme and to allow aggregation (see Cherchye *et al*., 2007; Van Puyenbroeck and Rogge, 2017). In this context, this DEA model has been also called the Benefit-of-the-Doubt (BoD) method proposed by Melyn and Moesen (1991)[18].

Let J be the number of countries evaluated in terms of R indicators. The respective index sets of countries and indicators are defined as $j = 1, \dots, J$, $r = 1, \dots, R$. For a country o, the basic BoD model can be formulated as follows:

$$
\begin{aligned}
& CI_o = max \sum_{r=1}^{R} \hat{u}_r y_{ro} \\
& \text{subject to} \\
& \sum_{r=1}^{R} \hat{u}_r y_{rj} \leq 1, \qquad j = 1, \dots, J \\
& \hat{u}_r \geq 0, \qquad r = 1, \dots, R
\end{aligned}
\tag{1}
$$

Where

CI_o	:	the value of composite indicator 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*.

[16] See Dyson and Shale (2010) for a non-technical overview concerning noise, uncertainty and measurement issues in DEA.

[17] Concerning all theoretical and methodological developments interested readers can also refer to Cazals *et al.* (2002) or Simar and Wilson (2011).

[18] See Rogge (2012) for a nice presentation of BoD Model.

The BoD-model (1) nicely illustrates the underlying 'Benefit-of-the-Doubt' concept. In the absence of information on the true weights, the model seeks for each entity the best set of weights which are used to aggregate the indicators into a composite index. The first restriction guarantees that no country can obtain a score larger than unity under these weights. The second constraint ensures that none of the weights will take a zero value[19]. The value of the composite index therefore lies in the interval [0,1]. Countries that achieve a score equal to unity are considered the least energy vulnerable of the sample; if the score is lower than unity, the country is considered the most energy vulnerable.

The conventional BoD model (1) assumes that indicators are measured on scales for which higher values indicate better composite indicators. Thus, indicators can be used only if they are all expressed in the same direction. Therefore, it proves to be inappropriate in cases where increases in some sub-indicator values entering in the CI construction are considered fortunate (hereafter 'desirable indicators') while increases in some others are considered unfortunate (hereafter 'reverse indicators'). Several approaches have been proposed to deal with this problem, such as data transformation techniques (e.g. normalization, rescaling or ranging normalization, translation, multiplicative inverse)[20]. The values of indicators for which value increases are not desirable are transformed to allow their treatment as desirable indicators. As pointed out by Färe *et al.* (2019) this can be problematic since the BoD model is not translation-invariant in the indicators. Moreover, the values of the composite indicator may be affected differently depending on the data transformation approach used (Liu and Sharp, 1999; Liu *et al.*, 2010).

The alternative approaches consider these reverse indicators as undesirable outputs (e.g. Zanella *et al.*, 2015a, 2015b). Insofar as these approaches are inspired by the traditional framework of Chung *et al.* (1997), the weak disposability of undesirable outputs is also assumed. Undesirable outputs can be decreased solely if they are accompanied by a simultaneous reduction in the desirable outputs, which is not relevant sometimes. Moreover, as pointed out by Färe *et al.* (2019), the assumption of null-jointness associated with these types of approaches (i.e. desirable outputs cannot be produced without producing some undesirable outputs) is difficult to justify in the context of the BoD model. Therefore, Färe *et al.* (2019) recently proposed an approach that uses a modified BoD model and a single version of the constant returns to scale DEA model. Unlike undesirable indicators, reverse indicators are not necessarily accompanied by desirable indicators, and a reduction in reverse indicator values does not automatically imply a reduction in desirable indicator values.

Let J be the number of countries evaluated in terms of R indicators partitioned into p desirable and $(R-p)$ reverse indicators. The respective index sets of countries, desirable and reverse indicators are defined as $j = 1, \dots, J$, $r = 1, \dots, p, \dots, R$. For a country o, following Färe *et al.* (2019), the conventional BoD model (1) considering both desirable and reverse indicators can be formulated as follows:

$$CI_o = max \sum_{r=1}^{p} \hat{u}_r y_{ro} - \sum_{r=p+1}^{R} \hat{u}_r y_{ro}$$

subject to

$$\sum_{r=1}^{p} \hat{u}_r y_{rj} - \sum_{r=p+1}^{R} \hat{u}_r y_{rj} \leq 1, \qquad j = 1, \dots, J$$

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

[20] See e.g. Scheel (2001) or Liu *et al.* (2010) for lists of data transformation techniques.

$$\hat{u}_r \geq 0, \qquad r = 1, \dots, p, \dots, R \tag{2}$$

Where

CI_o : the value of composite indicator 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*.

The main difference between (2) and (1) is that we seek to maximize the weighted sum of both desirable and reverse indicators, with the latter being subtracted from the former. Therefore, the model (2) allows us to gain in generality.

3.2.2 The Multi-Layer Benefit-of-the-Doubt model

In the DEA literature, several proposals of composite indicator construction have been made (see Zhou *et al.*, 2007; Cherchye *et al.*, 2007 or more recently Rogge, 2018). Most of them did not explicitly discuss the hierarchical structure of some composite indicators and thus did not propose a suitable model. One exception is the Multi-Layer Benefit-of-the-Doubt (MLBoD) proposed by Shen *et al*. (2013) on the basis of the multi-level data envelopment analysis model, initially proposed by Meng *et al*. (2008) and linearized in the same year by Kao (2008). Shen *et al.* (2013) state that the MLBoD model has more discriminating power than standard BoD-like models. Above all, the most important feature is thought to be the architecture of the model that suits studies involving multidimensional phenomena where hierarchical structures need to be explicit. In our study, given the hierarchical structure of the energy vulnerability composite index, we propose a modified MLBoD model with desirable and reverse indicators.

Let us consider additional information about the hierarchical structure of the composite index. Let J be the number of countries evaluated in terms of R indicators partitioned in p desirable and $(R-p)$ reverse indicators with a K-layered hierarchy. The respective index sets of countries, desirable and reverse indicators, and layers are defined as $j = 1, \dots, J$, $r = 1, \dots, p, \dots, R$ and $k = (1, \dots, K)$. Let $f_k = 1, \dots, R^{(k)}$ be the *f*th category in the *k*th layer where $R^{(k)}$is the number of categories in the *k*th layer. $R^{(1)} = R$, 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 modified MLBoD model can be formulated as follows:

$$\begin{aligned}
&CI_o = max \sum_{f_1=1}^{p} \hat{u}_{f_1} y_{f_1 o} - \sum_{f_1=p+1}^{R} \hat{u}_{f_1} y_{f_1 o} \\
&\text{subject to} \\
&\sum_{f_1=1}^{p} \hat{u}_{f_1} y_{f_1 j} - \sum_{f_1=p+1}^{R} \hat{u}_{f_1} y_{f_1 j} \leq 1, \qquad j = 1, \dots, J \\
&\hat{u}_{f_1} \geq 0, \qquad f_1 = 1, \dots, p, \dots, R
\end{aligned} \tag{3}$$

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 $y_{f_1 o}$: the value for country *j* and *o* respectively, on the indicators of the *f*th category in the first layer;

$R^{(k)}$: the number of categories in the *k*th layer

At this stage, for the evaluated country o, the model (3) estimates the weights $\hat{u}$ of the categories in the first layer. Since $R^{(1)} = R$, this model (3) is similar to the BoD model (2) i.e. the hierarchical structure of the 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 weight restrictions[21]. Following Shen *et al*. (2013) we consider upper and lower limits on corresponding internal weights associated with indicators of the *f*th category in *k*th layer, which sum to unity within a particular category[22]. Formally, we have $\sum_{f_1 \in A_{f_k}^k} \hat{u}_{f_1} / \sum_{f_1 \in A_{f_{k+1}}^{(k+1)}} \hat{u}_{f_1}$ where $A_{f_k}^k$ is the set of indicators of the *f*th category in the *k*th layer. By adding this restriction on weights to model (3), the model is now written as follows:

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

where *L* and *U* represent the lower and upper limits imposed on the corresponding internal weights. The goal is to aggregate the indicator values within a particular category of a particular layer by the weighted-sum approach in which the sum of the internal weights equals one.

4. RESULTS AND DISCUSSION

This section presents and discusses the results of the empirical analysis derived from program (4).

4.1. Index score and country ranking

The eight indicators, comprising of three desirable and four reserve indicators, were combined into a unique value. For each SIDS, the best possible indicator weights must be selected under a set of constraints. Five hundred replications were performed to derive robust MLBoD scores and rankings. The MLBoD results reflect relative vulnerability since the performance of a country is benchmarked on other countries' performances in the data set. Table 2 shows that Cape Verde scored the optimal score (1) while Papua-New-Guinea had the worst energy performance (0.2929). The performances of

[21] 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).

[22] 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.

SIDS on each indicator constitute the starting point for the identification of their relative strengths and weaknesses.

[Insert Table 2 here]

Figure 2 reports the final MLBOD values for SIDS. Countries are ranked from least vulnerable to most vulnerable. Cape Verde acts as a benchmark for underperforming countries to learn from best energy practices. Results should be carefully interpreted. An optimal score (1) under MLBoD represents a lower bound on vulnerability given the optimal set of weights assigned to each country. Cape Verde is the leader in this sample, indicating that the island is the least energy vulnerable island of the group. However, we cannot confirm that the latter is hardly vulnerable in absolute terms as we measure the relative energy vulnerability of SIDS, which is based on the respective performances of territories making up the sample.

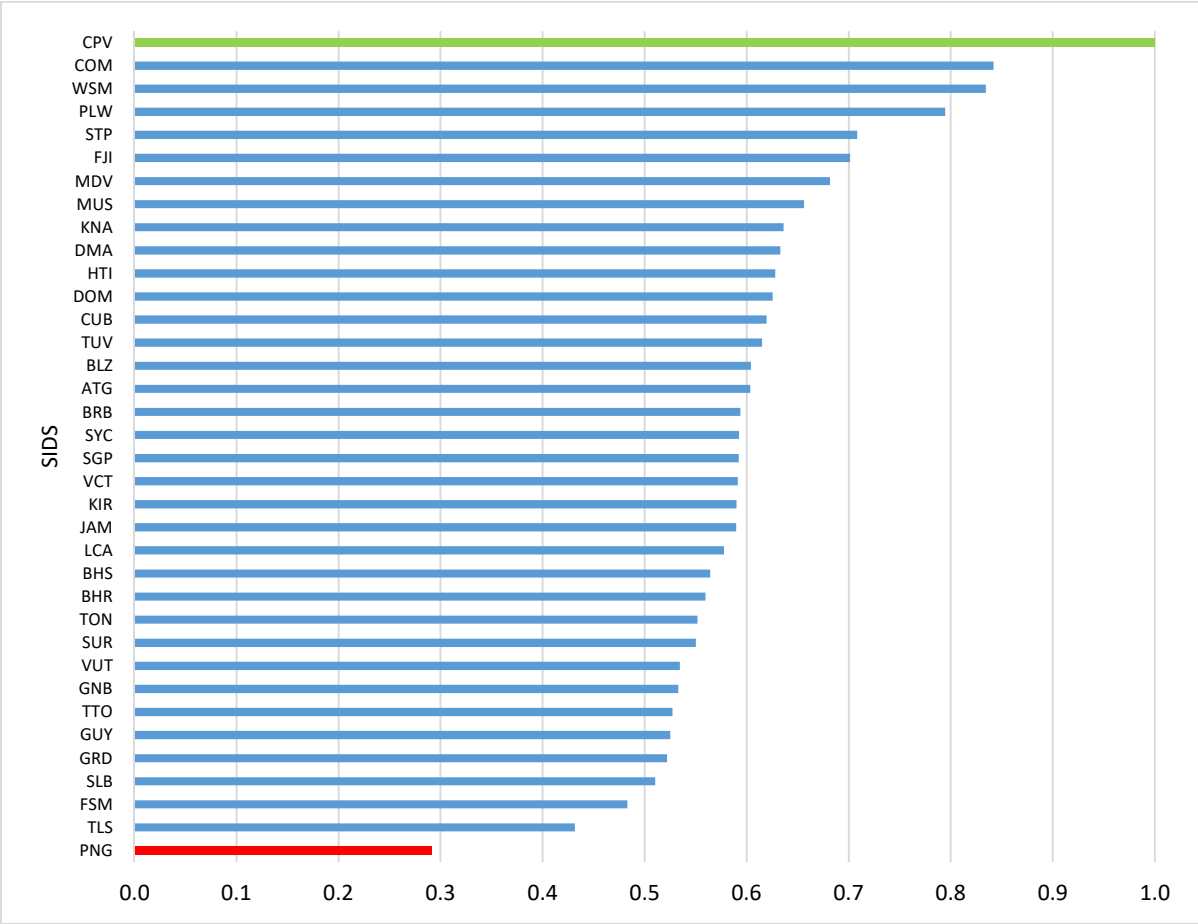

Fig. 2 Country ranking from least vulnerable (1) to most vulnerable (0.2929)
Source: authors
[To be printed in colour]

The set of weights, determined endogenously based on each country's relative performance, provides insights that can be considered in public policies. For those countries obtaining less favourable scores under MLBoD, the composite index acts as an incentive instead of a punishment for lagging countries to improve their overall performance. MLBoD provides useful benchmarks for lower ranking countries based upon a linear combination of observed best performances. Country scores and rankings are meaningful when comparing relative performances. However, more insights can be gained when composite indices are broken down and individual dimensions are analysed.

Each dimension and sub-index are represented and taken into account during the aggregation step. This holds for every SIDS in the data set. The relative contribution of each indicator (%) is based upon the weight assigned to that indicator. Contributions for each SIDS vary between 35% and 65% with 30% of flexibility[23]. This range constitutes the lower (L) and upper (U) bounds for the contribution of each indicator. The role of those dimensions contributing to energy vulnerability is discussed in more details in the following section.

4.2. Analysis of the contribution of dimensions to energy vulnerability

We study the relative contribution of dimensions in the computation of the energy vulnerability index to target the areas in which SIDS must make additional efforts in order to mitigate their relative vulnerability since the weighting scheme will enhance the dimensions in which the country is most efficient. The contribution of the exposure and shock sub-indices were 65% and 35% respectively for all SIDS, indicating that they were all relatively vulnerable on the shock aspect. The exposure component is no less important, however, since the more exposed a country is, the more likely it will be affected by the impacts of exogenous shocks.

In the following figure 3, SIDS were mapped according to the relative contribution of economic [EcoS thereafter] and environmental dimensions under the shock sub-index (vertical axis), and economic [EcoE thereafter] and social dimensions under the exposure sub-index (horizontal axis). If we look at Cape Verde (CPV) for instance, EcoE and the social dimension contributed 35% and 65% to exposure respectively while EcoS and the environmental dimension contributed 52% and 48% respectively. This means that it performed poorly on EcoS and to a lesser extent on the environmental dimension. Groups of SIDS emerge clearly based on the relative contribution of different dimensions to energy vulnerability, which enable us to gain useful insights for those SIDS having weaknesses on a specific dimension

[23] For the flexibility degree, we follow Shen et al. (2013) or Babaee et al. (2015).

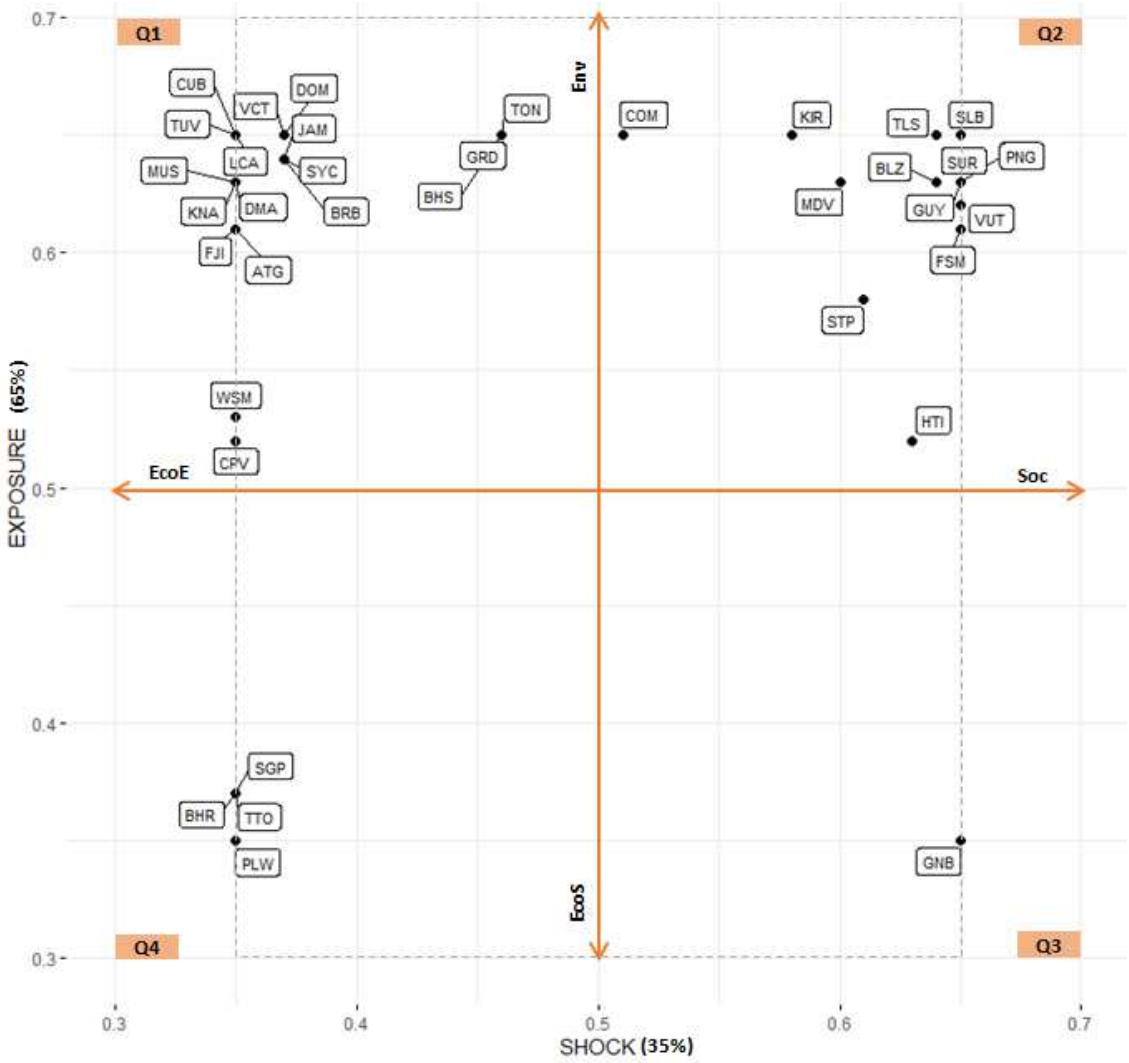

Fig. 3 The relative contribution of various dimensions to energy vulnerability for each SIDS
Source: authors
[To be printed in colour]

Regarding the shock sub-index, almost all SIDS (31 out of 36) had a lower contribution of the environmental dimension [Q1 and Q2] compared to EcoS [Q3 and Q4]. This means that for most countries, much of their vulnerability was due to the environmental dimension. In other words, their environmental performance was the lowest. Regarding the exposure sub-index, results were more heterogeneous: just over half (22 out of 36) had a lower contribution of EcoE [Q1 and Q4] compared to the social dimension (Q2 and Q3).

Taking these two dimensions into account, a country analysis can be carried out according to their weaknesses. We can then notice that half of the countries (18[24]) were grouped in quadrant 1 including the leader Cape Verde, thus pointing to a greater vulnerability on the following dimensions: CO2 content of primary energy (ENV3), energy import dependency (ECO13), energy mix diversity (ECO14), and overall system conversion efficiency (ECO16). However, when we consider each SIDS, vulnerability is not necessarily the product of the same dimensions as the distribution within

[24] Antigua and Barbuda, Bahamas, Barbados, Cape Verde, Cuba, Dominica, Dominican Rep., Fiji, Grenada, Jamaica, Mauritius, Samoa, Seychelles, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Tonga, and Tuvalu.

this quadrant shows. Indeed, we can see that Bahamas (BHS), Tonga (TON), and Grenada (GRD) had a lower contribution on the environmental dimension, which implies a greater vulnerability on this aspect. On the other hand, Samoa (WSM) and Cape Verde (CPV) had relatively similar contributions as regards both their economic and social dimensions. Their weaknesses were mainly due to their relative performance on the economic dimension of the exposure sub-index.

On the other side of the spectrum, only one country fell within quadrant 3. In fact, Guinea-Bissau (GNB) was among the least electrified SIDS, with only 15% of the population having access to electricity (SOC1) in 2015. GNB had a relatively high energy intensity of GDP (ECO5), thus indicating the lower contribution of EcoS. Conversely, it performed relatively well on the environmental dimension under the same sub-index while achieving good performances on EcoE. Indeed, GNB had the lowest energy dependency rate (ECO13) and the most efficient conversion system of the sample in that same year.

Another important group of SIDS (13[25]) are located in quadrant 2, showing that beside the environmental aspect, the social dimension should also be strengthened to reduce vulnerability. Disparities also exist in this quadrant: Haiti (HTI) must make additional efforts on the social dimension while Comoros (COM) must enhance its relative performance on the environmental dimension. It is interesting to note here that Comoros, ranked 2nd under MLBoD scores, did not belong to the same group as the leader CPV. This shows that it is possible to have low vulnerability as regards different factors. In fact, the good performance of CPV was mostly due to the environmental dimension whereas Comoros achieved a good score thanks to the economic dimension. It is therefore necessary to complete the analysis in terms of ranking by this contribution analysis to identify the dimensions that would be most likely help SIDS mitigate energy vulnerability.

The last quadrant (Q4) includes four SIDS[26] which were characterized by relatively better environmental and social performances compared to economic ones. Both economic dimensions under the exposure and sub-indices contributed more to their relative energy vulnerability. These SIDS had relatively high primary energy supply per capita (ECO1), especially Bahrain and Trinidad and Tobago. This group should therefore focus on improving energy efficiency to reduce energy consumption of the economy as a whole (ECO1 and ECO5).

To refine the analysis, we detail below the specific case of the leader (Cape Verde) and the laggard (Papua-New-Guinea).

4.3 The specific case of the leader and the laggard

Cape Verde is considered the reference country based on this particular sample and set of selected indicators. As a leader, Cape Verde provides scope for progress for those countries considered more vulnerable (scores lower than one) through its individual performance on each indicator of each dimension. This gives an interesting insight into the energy vulnerability mitigation efforts countries need to make based on the energy performances of the leader. Indeed, Cape Verde, although not having a 100% secure energy system, i.e. zero vulnerability, serves as the reference country for underperforming countries to benchmark best energy practices.

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[25] Belize, Comoros, Guyana, Haiti, Kiribati, Maldives, Micronesia, Papua-New-Guinea, Sao Tomé and Principe, Solomon Islands, Suriname, Timor-Leste, and Vanuatu.

[26] Bahrain, Palau, Singapore, and Trinidad and Tobago.

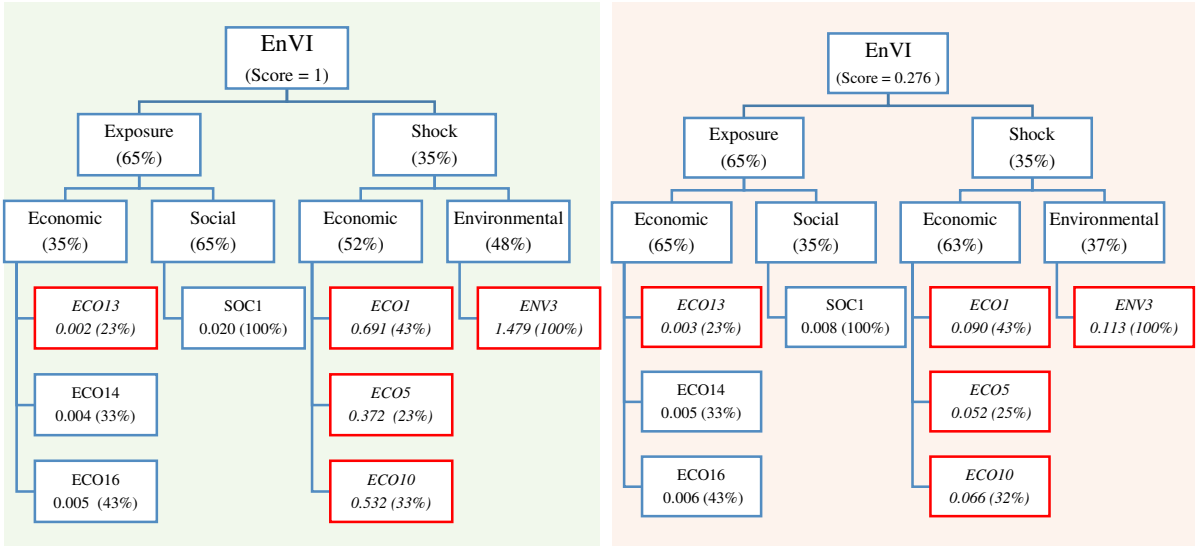

Fig. 4 Indicator weights (and shares) assigned to Cape Verde (left) and Papua-New-Guinea (right)
Source: authors
[To be printed in colour]

Figures 4 provides valuable insights in terms of indicator weights and contribution (%) in each category of each layer of the hierarchy for the leader and the laggard. More weight is allocated to 'reverse' (in italic) indicators since their weighted average will be subtracted from the weighted average of 'desirable dimensions', thus punishing relatively poor performances in those dimensions.

Weighting schemes are specific for each country and provide scope for improvement by means of public policies. Although Papua-New-Guinea has the most vulnerable energy system, the gap between Papua-New-Guinea and Cape Verde is not intractable. Understanding the performance of Cape Verde on each indicator is a first step towards improving Papua-New-Guinea's own overall performance. Cape Verde had relatively good performances on each indicator except for its energy dependency (ECO13).

Considering Papua-New-Guinea's overall performance, the island still needs to provide substantial efforts in several dimensions. Regarding the social dimension (SOC1), it achieved only 23% of electrification in 2015. Energy vulnerability concerns also relate to the environmental dimension (ENV3). Papua-New-Guinea's primary energy mix had a relatively high carbon content (2,084 ton CO_2 per toe against 0.477 ton CO_2 per toe for Cape Verde), mostly due to the presence of petroleum products. This is confirmed by the contribution of Papua-New-Guinea's dimension to its overall MLBoD score. Indeed, the social dimension (SOC1) contributed 35% while the environmental dimension (ENV3) contributed 37%. A lower contribution indicates that there is room for improvement in those targeted dimensions.

On the contrary, the laggard performed well on the economic dimension (ECO13), indicating that the island is relatively less dependent towards foreign imports of fossils (0.526 toe) fuels compared to the leader (1.324 toe). Moreover, Papua-New-Guinea had the most diversified primary energy mix of the sample. However, its outstanding performance on only one dimension was not sufficient to propel the island to a higher rank.

Overall, benchmarking on Cape Verde's performance, Papua-New-Guinea could improve the energy intensity of its economy as a whole (ECO5) with a particular attention to the transport sector (ECO10). Although having a relatively efficient conversion system, the use of more efficient

technologies could be a means to not only ensuring efficient conversion of primary energy into useful final energy, it could also promote a less energy intensive economy.

Departing from the above analysis, we provide some critical elements that should be considered and implemented in order to mitigate energy vulnerability in SIDS. We discuss the main implications of designing a composite index of energy vulnerability. Firstly, the hierarchical (or nested) structure of our composite index helps to improve our understanding of the factors that exacerbate energy vulnerability in these territories. Secondly, our composite index can serve as a decision-making tool, and thus has policy relevance for analysis and public communication. Indeed, benchmarking implies the identification of the most efficient unit (the least vulnerable in our case) as a target for underperforming SIDS.

Regarding energy vulnerability mitigation, structural transformation of island energy systems seems necessary. This can be done in several ways, depending on the factors that contribute the most to the relative vulnerability of each SIDS. Exposure to exogenous shocks can be detrimental to the proper functioning of small economies, particularly as regards economic growth and poverty reduction, issues that SIDS still struggle to tackle effectively. The design of a composite index is therefore an important step to aid policy makers in identifying priority areas.

In tackling energy vulnerability, it might be important to strike the right balance between exposure and impacts of shocks in order to lower the global impact of the two combined. Diversifying domestic energy (ECO14) mixes is often seen as a bulwark against exogenous shocks. A well-diversified energy mix might help to dampen the impact fluctuating energy prices on international markets, especially those of petroleum products. Diversification strategies may also lower the risk of disruption in their respective energy supply chain considering the concentration of fossil reserves in a few countries.

Technical and technological challenges also deserve attention. Some SIDS experienced heavy losses while converting primary energy into useful final energy (ECO16). The use of more efficient production technologies could enhance the conversion of primary energy into final energy, thus limiting losses overall. Relatively poor SIDS were still struggling to provide universal access to electricity (SOC1) to their population in 2015. International aid and regional cooperation are necessary to support SIDS in their transition to more resilient energy systems. This can be done through investment, technological transfers and technical assistance.

5. CONCLUSION

This paper proposes a composite index to assess energy vulnerability in small island developing states (SIDS) by means of a Multi-Layer Benefit-of-the-Doubt (MLBoD) approach. Our contributions to the existing literature are as follows: firstly, conceptual by the design of a composite index with a hierarchical structure. Secondly, methodological by the elaboration of the MLBoD approach that deals with desirable and reverse indicators. More precisely, we investigate the driving forces behind island energy systems vulnerability through a nested, hierarchical structure of the composite index.

Uncertainties around increases in energy demand, supply chain disruptions, fuel availability and prices, efficiency of technologies as well as environmental impacts of energy consumption are all factors that reinforce energy vulnerability concerns. There are obvious socio-economic disparities amongst SIDS. Understanding island energy system challenges becomes an essential part of energy planning and management. Ultimately, it constitutes a first step towards mitigating energy vulnerability.

We show that the composite index of energy vulnerability can be a useful tool for SIDS in terms of energy performance evaluation, benchmarking, and decision making. We then provide a classification that highlights differences in the patterns of energy practices of SIDS. The main lesson of this analysis indicates that a significant effort at the environmental level remains to be done for most SIDS. To a lesser extent, the economic aspect also needs to be addressed, with a general trend indicating that the respective energy mixes of SIDS are poorly diversified. Moreover, the heavy dependence on fossil fuels is detrimental to their energy systems due to increased exposure to exogenous shocks. In general, many SIDS also need to implement energy efficiency measures to optimize the transformation of primary energy into secondary energy. Minimizing losses on energy production, transmission and distribution chains could thus help SIDS to reduce to some extent the amount of energy used to operate socio-economic activities.

While this article focuses on SIDS, we insist that the tools described above for measuring energy vulnerability can be applied to other territories. However, we cannot generalize the results and conclusions to other territories at this stage. To be able to extend the study to other territories, it would require substantial data collection that goes beyond the scope of this study. However, this could be a research avenue to explore. Indeed, it would be interesting to identify the share of energy vulnerability due to SIDS intrinsic characteristics compared to other groups of countries. Future research could investigate the relative vulnerability of other groups of countries to overcome coverage concerns while exploring whether SIDS are more vulnerable than advanced or emerging economies. The composite index of energy vulnerability is not a stand-alone tool for vulnerability mitigation. Instead, we encourage the use of a composite index combined to other indicators of growth, development and progress to have a more global and enriched overview of the specificities of SIDS.

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Appendix A

Table A.1 Basic indicators for SIDS in 2015

Country	Code	Pop density [27] (pop/km^2)	GDP per cap ($ PPP)[28]	Status
Atlantic, Indian Ocean and South China Sea (AIMS)				
Singapore	SGP	7713,3	83342	NOI
Bahrain	BHR	1763,3	43927	NOE
Seychelles	SYC	206,5	24857	NOI
Mauritius	MUS	620,4	18879	NOI
Maldives	MDV	1516,4	12684	NOI
Cape Verde	CPV	130,2	6007	NOI
Sao Tomé and Principe	STP	207,7	2890	NOI
Guinea-Bissau	GNB	61,8	1474	NOI
Comoros	COM	417,8	2494	NOI
Caribbean				
Trinidad and Tobago	TTO	267,1	31460	NOE
Bahamas	BHS	37,4	29366	NOI
St. Kitts and Nevis	KNA	196,9	27179	NOI
Antigua and Barbuda	ATG	212,7	21426	NOI
Barbados	BRB	663,6	16396	NOI
Suriname	SUR	3,6	14488	NOE
Dominican Republic	DOM	212,8	13717	NOI
Grenada	GRD	322,4	12436	NOI
St. Lucia	LCA	293,7	11568	NOI
St. Vincent and the Grenadines	VCT	279,8	10472	NOI
Dominica	DMA	94,9	10215	NOI
Belize	BLZ	15,8	7977	NOI
Jamaica	JAM	266,9	8047	NOI
Guyana	GUY	3,9	7087	NOI
Cuba	CUB	108,9	6523	NOI
Haiti	HTI	388,1	1654	NOI
Pacific				
Palau	PLW	38,4	17132	NOI
Fiji	FJI	47,5	8776	NOI
Timor-Leste	TLS	80,5	7657	NOE
Samoa	WSM	68,4	5567	NOI
Tonga	TON	140,0	5477	NOI
Papua New Guinea	PNG	17,9	3820	NOE
Tuvalu	TUV	370,0	3389	NOI
Micronesia (Fed. States of)	FSM	155,6	3137	NOI
Vanuatu	VUT	22,2	2739	NOI
Solomon Islands	SLB	21,5	2094	NOI
Kiribati	KIR	136,9	1976	NOI

Source: authors

Note: NOI stands for net oil importer and NOE for net oil exporter

[27] Source: World Development Indicators of The World Bank and World Population Prospects: The 2019 revision

[28] Source: World Development Indicators of The World Bank, expressed in constant 2011 international $ PPP

Appendix B

Table B.1 Initial set of 21 variables

Dimension	Code	Name	E/S	Data source
Social	SOC1	Access to electricity	E	World Bank (SE4ALL)[29]; UN statistics (SDGs)[30]
	SOC2	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)[31]
	ECO2	Final energy intensity per capita	S	
	ECO4	Primary energy supply per unit of GDP	S**	
	ECO5	Final energy intensity of GDP	S	
	ECO7	Energy intensity in the agricultural sector	S	
	ECO8	Energy intensity in the service/commercial sector	S	
	ECO9	Energy intensity in the manufacturing sector	S	
	ECO10	Energy intensity in 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 generated	E	
	ECO13	Energy import dependency	E	UN Energy Balances (2015) [32]
	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 primary energy	S	EDGAR; UN Energy Balances (2015)

Note: TFEC stands for Total Final Energy Consumption; E stands for Exposure and S for Shock
*Based on d'Artigues and Vignolo (2012).

[29] https://datacatalog.worldbank.org/dataset/sustainable-energy-all (accessed on 18/03/2019)
[30] https://unstats.un.org/sdgs/indicators/database (accessed on 18/03/2019)
[31] https://unstats.un.org/unsd/snaama/downloads (accessed on 18/03/2019)
[32] https://read.un-ilibrary.org/natural-resources-water-and-energy/2015-energy-balances_5869b981-en#page1 (accessed on 18/03/2019)

Table B.2 Descriptive statistics of energy vulnerability variables (N = 36)

Code	Unit	Formula	Min	Max	Std. dev	Data sources
ECO1	*toe/cap*	TPES/population	0.16	14.22	2.760	United Nations Energy Balances 2015 edition; United Nations World Population Prospects : The 2019 Revision
ECO5	*toe/1 000 $ PPP*	TFC/GDP	0.013	0.319	0.061	United Nations Energy Balances 2015 edition; World Development Indicators of The World Bank
ECO10	*toe/1 000 $ PPP*	Energy use/Gross value added (transport)	0.072	2.07	0.399	United Nations Energy Balances 2015 edition; National Accounts Estimates of Main Aggregates
ECO13	*toe*	Energy imports/TPES	0.176	5.79	0.895	United Nations Energy Balances 2015 edition
ECO14	*toe*	$SWI = -\sum p_i ln(p_i)$	0	1.158	0.335	United Nations Energy Balances 2015 edition
ECO16	*%*	(TFC/TPES)*100	20.98	89.93	14.134	United Nations Energy Balances 2015 edition
ENV3	*ton CO_2/toe*	Total CO_2 emissions/TPES	0.44	5.48	1.322	EDGAR 2016 edition; United Nations Energy Balances 2015 edition
SOC1	*%*	% of population with access to electricity	14.66	100	24.474	The World Bank SE4ALL 2015

Note: (*) indicates that several countries the same value in a dimension.
U denotes undesirable, D denotes desirable indicators. S denotes shock and E denotes exposure
TPES stands for total primary energy supply, TFC stands for total final energy consumption
Total CO_2 emissions for Tuvalu were retrieved from the World Development Indicators of the World Bank for 2014.
*Based on d'Artigues and Vignolo (2012).

Appendix C

Table C.1: Eigenvalues and variance explained

	Eigenvalue	Variance (%)	Cum. variance (%)
Dim.1	6.6	31.5	31.5
Dim.2	4.4	21.1	52.5
Dim.3	2.3	10.8	63.3
Dim.4	1.6	7.6	70.9
Dim.5	1.5	7.2	78.1
Dim.6	1.3	6.4	84.5
Dim.7	1.0	4.7	89.2
Dim.8	0.6	2.9	92.1
Dim.9	0.5	2.2	94.3
Dim.10	0.4	2.0	96.3
Dim.11	0.3	1.3	97.6
Dim.12	0.2	1.0	98.5
Dim.13	0.1	0.6	99.1
Dim.14	0.1	0.3	99.4
Dim.15	0.0	0.2	99.7
Dim.16	0.0	0.2	99.8
Dim.17	0.0	0.1	99.9
Dim.18	0.0	0.1	100.0
Dim.19	0.0	0.0	100.0
Dim.20	0.0	0.0	100.0
Dim.21	0.0	0.0	100.0

Source: authors

Based on common practice, only those dimensions (or principal components – PC thereafter) with eigenvalues > 1 are kept. As we can see in table 1, the first seven dimensions all have eigenvalues greater than 1. Altogether, they explain 89% of total variance in the data set. Another way to select the number of PC to keep is through the analysis of the scree plot.

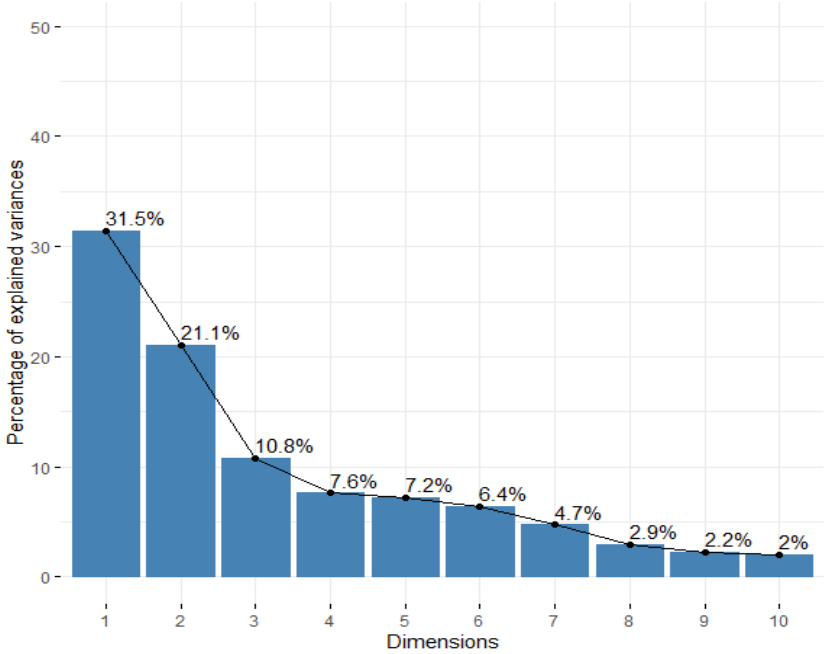

Fig. C.1 Scree plot where the break occurs after the third principal component
Source: authors

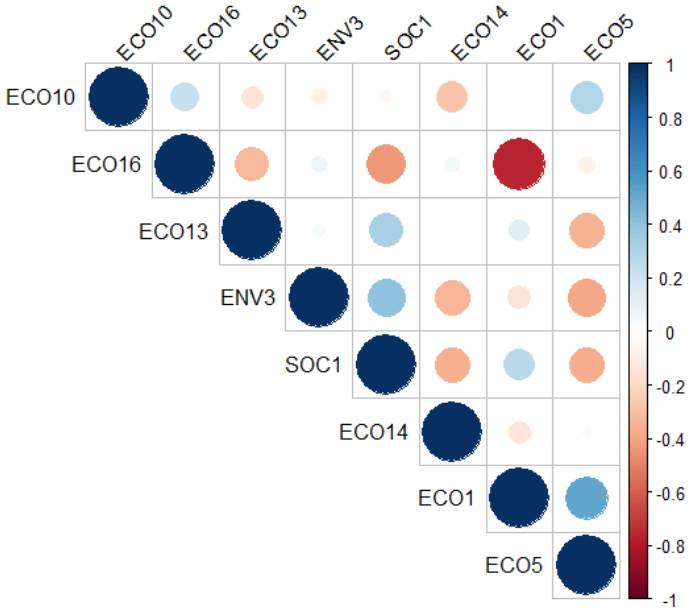

Fig. C.2 Correlogram of the final eight indicators
Source: authors

Appendix D

Table D.1 Raw data on the selected eight indicators for SIDS

	ECO1	ECO5	ECO10	ECO13	ECO14	ECO16	ENV3	SOC1
ATG	1.997	0.058	0.664	1.319	0.000	60.10	2.152	97.35
BHS	2.158	0.056	0.200	1.084	0.011	75.81	4.998	100
BHR	10.080	0.102	0.537	0.819	0.349	33.26	1.601	100
BRB	1.385	0.058	0.264	1.330	0.272	68.33	3.598	100
BLZ	0.979	0.102	0.772	0.613	0.962	82.61	2.891	92.21
CPV	0.398	0.049	0.326	1.324	0.606	74.31	0.477	92.61
COM	0.158	0.044	0.130	0.492	0.691	68.82	0.880	77.84
CUB	1.012	0.085	0.074	0.678	0.629	53.83	3.008	100
DMA	0.898	0.049	0.331	0.950	0.263	55.86	2.665	100
DOM	0.762	0.038	0.280	0.989	0.929	64.60	3.098	100
FJI	1.043	0.076	0.494	0.929	0.604	63.19	1.662	98.64
GRD	0.881	0.050	0.370	0.926	0.277	71.15	5.272	92.34
GNB	0.417	0.263	0.613	0.176	0.439	89.92	0.440	14.65
GUY	1.075	0.117	0.636	0.816	0.513	77.07	3.573	84.24
HTI	0.399	0.182	0.330	0.229	0.543	75.48	0.546	38.69
JAM	0.895	0.080	0.518	1.096	0.445	70.69	3.549	98.20
KIR	0.188	0.067	0.530	0.982	0.196	69.46	2.210	84.93
MDV	0.990	0.066	0.605	1.174	0.060	84.15	2.382	100
MUS	1.262	0.038	0.367	1.134	1.029	56.41	2.038	98.78
FSM	0.496	0.121	2.071	1.007	0.076	73.09	2.785	75.43
PLW	4.240	0.184	1.702	1.204	0.000	73.08	0.485	99.28
PNG	0.468	0.090	0.633	0.526	1.158	72.85	2.084	22.93
KNA	1.564	0.032	0.278	1.054	0.061	55.35	2.323	100
LCA	0.804	0.045	0.237	1.027	0.078	63.24	3.871	97.76
VCT	0.734	0.052	0.457	0.953	0.224	72.41	4.149	100
WSM	0.693	0.096	0.660	0.837	0.657	73.86	1.103	100
STP	0.321	0.081	0.333	0.780	0.715	72.86	0.876	65.44
SYC	1.584	0.044	0.220	2.403	0.063	67.92	3.452	100
SGP	5.266	0.037	0.072	5.861	0.792	35.80	1.648	100
SLB	0.240	0.098	0.094	0.518	0.701	83.89	2.057	55.10
SUR	1.257	0.069	0.629	0.790	0.574	79.26	3.320	87.17
TLS	0.159	0.013	0.466	0.906	0.349	61.08	2.356	63.39
TON	0.396	0.057	0.830	1.117	0.110	75.64	5.481	97.02
TTO	14.218	0.319	0.368	0.210	0.294	20.98	1.811	100
TUV	0.308	0.056	0.644	0.951	0.195	61.53	3.221	99.42
VUT	0.253	0.080	0.410	0.835	0.700	84.25	1.748	57.82

Source: authors

Appendix E

Table E.1 Confidence intervals for SIDS MLBoD scores

	MLBoD score	Lower bound	Upper bound
Cape Verde	1.0000	1.0000	1.0000
Comoros	0.8427	0.7758	0.9079
Samoa	0.8377	0.7537	0.9150
Palau	0.7979	0.7177	0.8713
Fiji	0.7183	0.6160	0.7870
Sao Tome and Principe	0.7119	0.6220	0.7946
Maldives	0.6899	0.6262	0.7369
Mauritius	0.6661	0.5984	0.7139
St. Kitts and Nevis	0.6433	0.5919	0.6805
Dominica	0.6401	0.5889	0.6769
Haiti	0.6328	0.5198	0.7363
Dominican Rep.	0.6322	0.5860	0.6652
Cuba	0.6256	0.5811	0.6577
Tuvalu	0.6217	0.5769	0.6536
Antigua and Barbuda	0.6099	0.5634	0.6435
Belize	0.6097	0.5687	0.6396
Kiribati	0.6000	0.5337	0.6467
Singapore	0.5987	0.5511	0.6333
Barbados	0.5986	0.5646	0.6231
Seychelles	0.5973	0.5627	0.6224
St. Vincent and the Grenadines	0.5959	0.5627	0.6197
Jamaica	0.5947	0.5588	0.6204
St. Lucia	0.5822	0.5501	0.6055
Bahamas	0.5680	0.5439	0.5851
Bahrain	0.5638	0.5356	0.5837
Tonga	0.5553	0.5308	0.5726
Suriname	0.5545	0.5241	0.5763
Vanuatu	0.5435	0.4887	0.5804
Guinea-Bissau	0.5409	0.4314	0.6345
Trinidad and Tobago	0.5304	0.5118	0.5427
Guyana	0.5289	0.5021	0.5481
Grenada	0.5252	0.5030	0.5408
Solomon Islands	0.5181	0.4702	0.5508
Micronesia	0.4866	0.4601	0.5059
Timor-Leste	0.4356	0.4055	0.4580
Papua New Guinea	0.2929	0.2793	0.3029

Source: authors

Appendix F

Table F.1 Contribution (%) of dimensions and sub-indices to energy vulnerability

	Sub-components		Exposure		Shock	
	Exposure	Shock	D1	D2	D3	D4
ATG	65%	35%	35%	65%	61%	39%
BHS	65%	35%	46%	54%	65%	35%
BHR	65%	35%	35%	65%	37%	63%
BRB	65%	35%	37%	63%	64%	36%
BLZ	65%	35%	64%	36%	63%	37%
CPV	65%	35%	35%	65%	52%	48%
COM	65%	35%	51%	49%	65%	35%
CUB	65%	35%	35%	65%	65%	35%
DMA	65%	35%	35%	65%	63%	37%
DOM	65%	35%	37%	63%	65%	35%
FJI	65%	35%	35%	65%	61%	39%
GRD	65%	35%	46%	54%	65%	35%
GNB	65%	35%	65%	35%	35%	65%
GUY	65%	35%	65%	35%	63%	37%
HTI	65%	35%	63%	37%	52%	48%
JAM	65%	35%	37%	63%	64%	36%
KIR	65%	35%	58%	42%	65%	35%
MDV	65%	35%	60%	40%	63%	37%
MUS	65%	35%	35%	65%	63%	37%
FSM	65%	35%	65%	35%	61%	39%
PLW	65%	35%	35%	65%	35%	65%
PNG	65%	35%	65%	35%	63%	37%
KNA	65%	35%	35%	65%	63%	37%
LCA	65%	35%	35%	65%	65%	35%
VCT	65%	35%	37%	63%	65%	35%
WSM	65%	35%	35%	65%	53%	47%
STP	65%	35%	61%	39%	58%	42%
SYC	65%	35%	37%	63%	64%	36%
SGP	65%	35%	35%	65%	37%	63%
SLB	65%	35%	65%	35%	65%	35%
SUR	65%	35%	65%	35%	63%	37%
TLS	65%	35%	64%	36%	65%	35%
TON	65%	35%	46%	54%	65%	35%
TTO	65%	35%	35%	65%	37%	63%
TUV	65%	35%	35%	65%	65%	35%
VUT	65%	35%	65%	35%	62%	38%

Source: authors
Note: Contribution is determined based on indicator weights.