



Benchmarking and Performance Evaluation Towards the Sustainable Development of Regions in Taiwan: A Minimum Distance-Based Measure with Undesirable Outputs in Additive DEA

Shih-Heng Yu¹

Accepted: 8 February 2019 / Published online: 18 February 2019
© Springer Nature B.V. 2019

Abstract

Sustainable development (SD) governance for a better society has received considerable attention. The development of a robust benchmarking and performance evaluation approach is a matter of growing concern to accelerate the progress in achieving SD. In this study, a minimum distance-based additive data envelopment analysis model with window analysis is proposed to attain the closest benchmarking target in the presence of undesirable outputs. This novel extension not only focuses on the construction of a composite indicator to shed light on the efficiency of each decision-making unit but also provides convincing and realizable suggestions for improving efficiency. This study benchmarks the SD efficiency across 19 administrative regions of Taiwan covering the period from 2011 to 2016. The empirical results reveal that the average SD efficiency of Taiwan has experienced a gradual deterioration over the last 3 years, and the primary sources of regional SD inefficiency may vary with industrial structure. Potential directions of improvement for reinforcing sustainable practices in Taiwan are also discussed. The findings can provide local governments with holistic insights into the sources that degrade SD performance and further contribute to improving SD solutions by recommending appropriate policies to achieve a more sustainable society.

Keywords Performance evaluation · Data envelopment analysis (DEA) · Closest benchmarking target · Undesirable outputs · Sustainable development · Sustainable society

1 Introduction

With the continuing threats of global climate change, resource exhaustion and ecological disruption, sustainable development (SD) has received unprecedented attention from the international community. The concept of SD emerged in 1987 with the publication of

✉ Shih-Heng Yu
shihhengyu@gmail.com; shyu@nuist.edu.cn

¹ Business School, Nanjing University of Information Science & Technology, Nanjing 210044, Jiangsu, China

the World Commission on Environment and Development (WCED), *Our Common Future* (commonly referred to as the Brundtland Report) (WCED 1987), which became a primary driver for the United Nations Conference on Environment and Development (UNCED) (also known as the Rio Earth Summit) in 1992 and the United Nations Conference on Sustainable Development (UNCSD) (commonly called Rio+20 Earth Summit) in 2012. To date, SD has been recognized as an overarching principle for long-term global development, and many countries have also placed their focuses on planning concrete policies to embody the core of SD and thereby create a better society (Rondinelli and Berry 2000).

SD consists of three essential dimensions, namely, economic, environmental and social, which are the so-called “three pillars of sustainability” or the “triple bottom line” (Elkington 1998; Holling 2001). As an instrument that harmonises economic and environmental dimensions, eco-efficiency has been launched with the aim of creating more value with less environmental (ecological) impact via the implementation of SD (WBCSD 2005). Specifically, eco-efficiency can be formulised as a ratio of economic output to environmental impact in which the indicators gross domestic product (GDP), value of products/services, sales and value added are general proxies for economic output while the indicators energy, material and water consumption; greenhouse gas (GHG) emissions; and waste pollution are general proxies for environmental impact (Schaltegger and Sturm 1990; Michelsen et al. 2006; Wursthorn et al. 2011; Wang et al. 2015). Although eco-efficiency might guide a practical solution for SD, eco-efficiency analyses do not guarantee sustainability because they cover only economic and environmental dimensions (Bruni et al. 2011; Charmondusit et al. 2014). A broadened eco-efficiency analysis that incorporates the social dimension was recently recommended to thoroughly achieve SD core concepts via benchmarking (Tatari et al. 2016; Caiado et al. 2017; Nissi and Sarra 2018).

Developing a robust SD measure composed of multiple indicators related to all three dimensions is of vital importance for achieving improvements towards sustainability (Jollands et al. 2004; Strezov et al. 2017). In order to address this issue, data envelopment analysis (DEA), introduced by Charnes et al. (1978) based on the earlier work of Farrell (1957), has received wide recognition. DEA is a widely used non-parametric approach to assessing the relative efficiencies of a set of homogenous decision-making units (DMUs) that consume multiple inputs to produce multiple outputs. The important feature of DEA is that it not only objectively provides a composite indicator to ascertain the efficiency of each DMU but also offers benchmarking information to elucidate strategies for improving the efficiency of inefficient DMUs. Research in the SD fields has witnessed a great acceptance of the DEA (Zhou et al. 2018). For example, Bruni et al. (2011) employed DEA to benchmark the SD performance of 20 Italian regions in which several indicators involving energy consumption, GDP, carbon dioxide (CO₂) emissions and the poverty rate were considered. Lee and Farzipoor Saen (2012) advanced the measurement of corporate sustainability management performance in the Korean electronics industry using DEA. Yin et al. (2014) focused on the topic of urban sustainability and applied DEA to investigate the SD performance of 30 provincial capital cities in China. As for the electricity industry, Tajbakhsh and Hassini (2018) developed a comprehensive measure for sustainability performance of fossil-fuel power plants in the U.S.

Generally, DEA has two fundamental types of models, namely, radial and non-radial. Classic DEA models, such as CCR (Charnes–Cooper–Rhodes) (Charnes et al. 1978) and BCC (Barker–Charnes–Cooper) (Banker et al. 1984), are referred to as radial models and mainly deal with changes in either inputs or outputs in a proportional way, whereas the additive DEA (Charnes et al. 1985), the enhanced Russell measure (Pastor et al. 1999) and the slacks-based measure (Tone 2001) are well-known non-radial models that allow changes in

both inputs and outputs in different proportions. Moreover, some extensions of DEA, which allow for both input contraction and output expansion in the direction of a given input–output vector, have been developed in accordance with the directional distance function (DDF) presented by Chambers et al. (1996). From this perspective, existing DEA variants can be clearly partitioned in the direct approach (using DDF) and the indirect approach (not using DDF) (Zanella et al. 2015). Here, I build on the additive DEA which is considered an indirect approach, and devote into its possible reinforcement to regional SD applications. The additive DEA model has a greater discriminatory power and excels in identifying the sources of inefficiency and yielding efficiency scores that are coherent with the Pareto–Koopmans optimality notion, which may be appropriate for the current study (Zhou et al. 2007; Du et al. 2010). However, the additive DEA model may generate an unconvincing projection (or benchmarking target) that is far away from the DMU under evaluation. This imperfection stems from the fact that the model attempts to maximize the potential contraction of inputs and expansion of outputs. Additionally, the other notable defect of the additive DEA model lies in the fact that it does not consider undesirable outputs.

To address the aforementioned gap of additive DEA and focus on the holistic assessment of regional SD, this study has two main objectives. First, this study proposes a minimum distance-based additive DEA model with window analysis that accommodates the undesirable outputs and provides the closest benchmarking target for each considered DMU. The second objective is to evaluate the longitudinal SD efficiency across 19 administrative regions of Taiwan over a period from 2011 to 2016, aiming to provide local governments with directions of improvement towards a more sustainable society. Taiwan is a mountainous island in East Asia and holds a population of approximately 23 million spread across a total land area of nearly 36,000 km²; it is one of the most densely populated places in the world and has very limited natural resources. Since the 1960s, Taiwan has experienced rapid economic growth along with substantial progress in industrialisation. This trend has consequently resulted in high energy consumption and impacts to the diversified ecology, natural environment and quality of human life. The Executive Yuan, which is the executive branch of the central government of Taiwan, organised the National Council for Sustainable Development (NCSO) in 1997 to combat these obstacles to SD and spearhead national SD by formulating regulations for the Sustainable Development Action Plan (NCSO 2009). Currently, a primary task of the NCSO in Taiwan is to achieve international SD standards, especially the 17 Sustainable Development Goals (SDGs) of the 2030 Agenda announced by the United Nations (UN 2015). However, the success of SD promotion is highly dependent on the conjunction of SD implementation in cities and counties since these subnational scales act as key pioneers in localizing sustainability (Gibbs 1998; Herrera-Ulloa et al. 2003; Lebel et al. 2006). Thus, developing a method of properly assessing regional SD performance to promote sustainability among cities and counties has become one of the most crucial topics in Taiwan. The benchmarking results obtained in the present research framework not only enable local governments in cities and counties to clearly understand the current state of SD promotion from an efficiency perspective but also offer potential directions to guide the development of appropriate policies for improvements that contribute to localize and realize the goal of SD.

The rest of this paper is arranged as follows. The next section reviews the radial and additive DEA models. Section 3 introduces the proposed additive model and explains how it can be adopted herein to carry out longitudinal SD evaluation for the subsequent study. The research sample and data collection are presented in Sect. 4. Section 5 elaborates the empirical results and discussions with respect to regional SD efficiency in Taiwan. Finally, concluding remarks are drawn in the last section.

2 Data Envelopment Analysis

The primary feature of DEA is the proverbial capability to compose an objective indicator for each DMU having multiple inputs and multiple outputs. This indicator, termed as efficiency, represents the DMU’s distance to an efficient frontier and can be assessed at industrial (Belu 2009; Sun and Stuebs 2013; Mahdiloo et al. 2015; Wang et al. 2016), regional (Liu et al. 2010; González et al. 2011; Yin et al. 2014; Carboni and Russu 2015), and national levels (Zhou et al. 2010; Wu et al. 2014a, b; Rashidi and Farzipoor Saen 2015; Gómez-Calvet et al. 2016). The efficient frontier acts as the boundary of the Production Possibility Set (PPS) spanned by all observed DMUs. This section briefly reviews radial and additive DEA models and explains how they perform the task of performance evaluation.

2.1 Radial DEA Model

Suppose that there are n homogenous DMUs, each of which consumes m inputs to produce s outputs. For the j th DMU, $j = 1, \dots, n$, let x_{ij} and y_{rj} denote the i th input, $i = 1, \dots, m$, and r th output, $r = 1, \dots, s$, respectively. The radial CCR model, which was originally proposed by Charnes et al. (1978), for evaluating the input-oriented efficiency of DMU_o under constant returns to scale (CRS) is given as follows.

$$\begin{aligned}
 & \min \quad \theta_o \\
 & \text{s.t.} \\
 & \sum_{j=1}^n \lambda_j x_{ij} \leq x_{io} \theta_o \quad i = 1, \dots, m \\
 & \sum_{j=1}^n \lambda_j y_{rj} \geq y_{ro} \quad r = 1, \dots, s \\
 & \lambda_j \geq 0 \quad j = 1, \dots, n
 \end{aligned} \tag{1}$$

where λ_j is a non-negative variable representing the intensity of the j th DMU in forming the efficient frontier and θ_o represents a proportional scale for the inputs contraction of a DMU_o . Denote the optimality of model (1) by superscript “*”, and the efficiency of DMU_o can be defined as θ_o^* which ranges from 0 to 1. Obviously, if $\theta_o^* = 1$, then DMU_o is efficient and lies on the efficient frontier; otherwise, it is inefficient and is at a distance from the efficient frontier. Model (1) can be extended to meet with variable returns to scale (VRS) assumption (known as the BCC model) by imposing the constraint $\sum_{j=1}^n \lambda_j = 1$ (Banker et al. 1984).

One should note that a $DMU_o(x_{io}, y_{ro})$ with $\theta_o^* = 1$ may be weakly efficient, i.e., there exists $(-x'_i, y'_r) \in PPS \geq (-x_{io}, y_{ro})$ and $(x'_i, y'_r) \neq (x_{io}, y_{ro})$. Moreover, for inefficient DMUs, the suggested improvements to reach the efficient frontier, i.e., contraction on all inputs, rely on a unified scale $1 - \theta_o^*$. In addition to input-oriented model (1), there is also output-oriented model that mainly deals with the expansion of outputs [for more details please refer to Charnes et al. (1978)]. The efficiency with such radial measures, however, can be assessed only from either input-oriented or output-oriented sides.

2.2 Additive DEA model

These problems can be solved by taking non-radial slacks into account. Charnes et al. (1985) developed the following additive DEA model to simultaneously tackle both input and output slacks, such that the inputs and outputs of a DMU_o can be contracted and expanded in different proportions.

$$\begin{aligned}
 &\max \quad \sum_{i=1}^m s_{io}^- + \sum_{r=1}^s s_{ro}^+ \\
 &\text{s.t.} \\
 &\quad \sum_{j=1}^n \lambda_j x_{ij} = x_{io} - s_{io}^- \quad i = 1, \dots, m \\
 &\quad \sum_{j=1}^n \lambda_j y_{rj} = y_{ro} + s_{ro}^+ \quad r = 1, \dots, s \\
 &\quad \lambda_j \geq 0, s_{io}^- \geq 0, s_{ro}^+ \geq 0 \quad j = 1, \dots, n
 \end{aligned} \tag{2}$$

where s_{io}^- and s_{ro}^+ are the non-radial slacks for DMU_o 's i th input and r th output, which represent the excess amounts of the i th input and the shortage amounts of the r th output compared with the efficient frontier, respectively. If in optimal solution of model (2) for DMU_o one has that $s_{io}^- = 0$ and $s_{ro}^+ = 0$ for all i and r , then DMU_o is efficient; otherwise, it is inefficient and has the room on $s_{io}^- \neq 0$ and/or $s_{ro}^+ \neq 0$ should be adjusted. The benchmarking target $(\bar{x}_{io}, \bar{y}_{ro})$ of DMU_o on the efficient frontier can be determined by $(x_{io} + s_{io}^{*-}, y_{ro} + s_{ro}^{*+})$ or $(\sum_{j=1}^n \lambda_j^* x_{ij}, \sum_{j=1}^n \lambda_j^* y_{rj})$. The reference set is given as $B_o = \{DMU_j | \lambda_j^* > 0, j = 1, 2, \dots, n\}$, indicating which DMU_j serves as a benchmark for inefficient DMUs.

The optimal objective value of model (2) is a sum of input and output slacks rather than an explicit efficiency measure. For DMU_o , the additive efficiency ρ_o^* can be defined as follows (Tone 2001).

$$\rho_o^* = \frac{1 - \frac{1}{m} \sum_{i=1}^m s_{io}^{*-} / x_{io}}{1 + \frac{1}{r} \sum_{r=1}^s s_{ro}^{*+} / y_{ro}} \tag{3}$$

Notably, the ρ_o^* ranges between 0 and 1 and is unit-invariant. Moreover, ρ_o^* is monotonically decreasing with respect to $s_{io}^{*-} = 0$ and $s_{ro}^{*+} = 0$; that is, a larger value of ρ_o^* indicates a better performance. An efficient DMU_o with $\rho_o^* = 1$ is strongly Pareto-efficient, which is achieved if and only if $s_{io}^{*-} = 0$ and $s_{ro}^{*+} = 0$.

3 A minimum distance-based additive model with undesirable outputs

The general efficiency criterion of production processes associated with the aforementioned models is a matter of how DMUs consume as less amounts of each input as possible to produce as more amounts of each output as possible. However, in many real-world situations, undesirable outputs would inescapably appear as by-products accompanied with desirable outputs (Scheel 2001; Seiford and Zhu 2002; Zhou et al. 2007). Therefore, measuring efficiency in the presence of undesirable outputs has attracted considerable attention in the literature, especially in the fields of energy, ecology and environment (Tyteca 1996; Chung et al. 1997; Lozano and Gutierrez 2008). In this section, the additive model (2) was first extended to incorporate undesirable outputs, and then a novel minimum distance-based additive model under the window analysis procedure was proposed to find the closest benchmarking targets and perform a longitudinal efficiency assessment.

3.1 Incorporating undesirable outputs into additive DEA

Different models have been proposed to handle the undesirable outputs under the strongly disposable assumption. One method applies a non-linear monotonic decreasing transformation that takes the multiplicative inverse of the undesirable outputs, i.e., $f(U) = 1/U$ (Golany and Roll 1989; Lovell et al. 1995). Another is built on linear monotonic decreasing transformation, which adds absolute constants to the opposite of undesirable outputs, i.e., $f(U) = -U + B$ (Ali and Seiford 1990; Scheel 2001; Seiford and Zhu 2002). The other one, suggested by Reinhard et al. (1999), is to treat undesirable outputs as inputs, and it has received considerable acceptance in recent studies (e.g., Hailu and Veeman 2001; Yang and Pollitt 2009; Mahlberg and Sahoo 2011; Sahoo et al. 2011; Wu et al. 2014a, b). It should be noted that these methods are regarded as indirect approaches (Zanella et al. 2015). As for direct approaches, Chung et al. (1997) employed DDF to simultaneously deal with the joint production of desirable and undesirable outputs. Despite the increased popularity for the adoption of Chung et al.'s (1997) method, it remains difficult to explicitly assign the justified direction vector (Wang et al. 2017).

This study adopts the method of considering undesirable output as inputs since it is readily understood and does not require actual data transformation. Assume that each DMU_{*j*}, $j = 1, 2, \dots, n$, consumes m inputs x_{ij} , $i = 1, \dots, m$, to produce q_1 desirable outputs $y_{r_1j}^g$, $r_1 = 1, \dots, q_1$, along with q_2 undesirable outputs $y_{r_2j}^b$, $r_2 = 1, \dots, q_2$. The additive model that can deal with undesirable outputs is given as follows.

$$\begin{aligned}
 & \max \quad \sum_{i=1}^m s_{io}^- + \sum_{r_1=1}^{q_1} s_{r_1o}^{+g} + \sum_{r_2=1}^{q_2} s_{r_2o}^{+b} \\
 & \text{s.t.} \\
 & \quad \sum_{j=1}^n \lambda_j x_{ij} = x_{io} - s_{io}^- \quad i = 1, \dots, m \\
 & \quad \sum_{j=1}^n \lambda_j y_{r_1j}^g = y_{r_1o}^g + s_{r_1o}^{+g} \quad r_1 = 1, \dots, q_1 \\
 & \quad \sum_{j=1}^n \lambda_j y_{r_2j}^b = y_{r_2o}^b - s_{r_2o}^{+b} \quad r_2 = 1, \dots, q_2 \\
 & \quad \lambda_j \geq 0, s_{io}^- \geq 0, s_{r_1o}^{+g} \geq 0, s_{r_2o}^{+b} \geq 0 \quad j = 1, \dots, n
 \end{aligned} \tag{4}$$

where $s_{i_o}^-$, $s_{r_1o}^{+g}$ and $s_{r_2o}^{+b}$ represent the excess for i th input, shortage for r_1 th desirable output and overproduction for r_2 th undesirable output of the DMU_{*o*}, respectively. By adding the convexity constraint $\sum_{j=1}^n \lambda_j = 1$, the additive model under the VRS assumption is achieved. As in model (4), the undesirable outputs hold the same property as the inputs, i.e., the less the better, and both $s_{i_o}^-$ and $s_{r_2o}^{+b}$ represent how much of the adjusted amount should be decreased to improve DMU_{*o*}'s performance status. Thus, for DMU_{*o*}, the benchmarking target $(\bar{x}_{i_o}, \bar{y}_{r_1o}^g, \bar{y}_{r_2o}^b)$ can be defined as $(x_{i_o} - s_{i_o}^{-*}, y_{r_1o}^g + s_{r_1o}^{+g*}, y_{r_2o}^b - s_{r_2o}^{+b*})$.

3.2 Closest benchmarking target and minimum distance-based measure

As model (4) maximizes the sum of $s_{i_o}^-$, $s_{r_1o}^{+g}$ and $s_{r_2o}^{+b}$, the obtained benchmarking target $(\bar{x}_{i_o}, \bar{y}_{r_1o}^g, \bar{y}_{r_2o}^b)$ is the farthest one and may not be sufficiently convincing to serve as a reference for inefficient DMUs. To process a more practical assessment by finding the closest benchmarking target, the maximization may be replaced by a minimization for the objective function; however, the resultant model is unbounded if one does so.

Previous work conducted by Aparicio et al. (2007) found that the closest benchmarking target on the efficient frontier for DMU_{*o*} can be sought by embedding the linear combination of extremely efficient DMUs from the envelopment form and the weights regarding inputs and outputs from the multiplier form into constraints. Geometrically, extremely efficient DMUs are vertices of the facets of the efficient frontier, and each is not a linear combination of the other DMUs (Sueyoshi and Sekitani 2007). As reported in Aparicio et al. (2007), the idea of similarity between evaluated DMU_{*o*} and benchmarking target can be achieved by different criteria, including distance and efficiency measure, thereby conceiving several possible variants. For example, to generate closest targets, the L_1 -distance, L_2 -distance and L_∞ -distance can be adopted. Otherwise, if the efficiency measure criterion is used, models with the maximization of efficiency measure at the objective function such as the range adjusted measure (Cooper et al. 1999), the enhanced Russell measure (Pastor et al. 1999), and the slacks-based measure (Tone 2001) can be also formulated.

Let $E = \{DMU_k \in J | s_{i_o}^{-*}, s_{r_1o}^{+g*}, s_{r_2o}^{+b*} = 0, \lambda_k^* = 1, \lambda_j^* = 0, \forall j \neq k\}$ denote the set of extremely efficient DMUs as a subset of a whole DMU set $J \in \{1, \dots, n\}$ using the optimal solution for the model (4) (Charnes et al. 1986, 1991). Based on the mDD model of Aparicio et al. (2007), this study proposes the minimum distance-based additive DEA model as a form of 0–1 mixed integer linear programming (MILP) to find the closest benchmarking targets in the presence of undesirable outputs, expressed as follows:

$$\begin{aligned}
 \min \quad & \sum_{i=1}^m s_{io}^- + \sum_{r_1=1}^{q_1} s_{r_1o}^{+g} + \sum_{r_2=1}^{q_2} s_{r_2o}^{+b} \\
 \text{s.t.} \quad & \sum_{j \in E} \lambda_j x_{ij} = x_{io} - s_{io}^- \quad i = 1, \dots, m \\
 & \sum_{j \in E} \lambda_j y_{r_1j}^g = y_{r_1o}^g + s_{r_1o}^{+g} \quad r_1 = 1, \dots, q_1 \\
 & \sum_{j \in E} \lambda_j y_{r_2j}^b = y_{r_2o}^b - s_{r_2o}^{+b} \quad r_2 = 1, \dots, q_2 \\
 & - \sum_{i=1}^m v_i x_{ij} + \sum_{r_1=1}^{q_1} u_{r_1} y_{r_1j}^g - \sum_{r_2=1}^{q_2} z_{r_2} y_{r_2o}^b + d_j = 0 \\
 & v_i \geq 1, u_{r_1} \geq 1, z_{r_2} \geq 1 \quad j \in E \\
 & d_j \leq Mb_j \\
 & \lambda_j \leq M(1 - b_j) \\
 & b_j \in \{0, 1\} \\
 & \lambda_j \geq 0, d_j \geq 0, s_{io}^- \geq 0, s_{r_1o}^{+g} \geq 0, s_{r_2o}^{+b} \geq 0
 \end{aligned} \tag{5}$$

where s_{io}^- , $s_{r_1o}^{+g}$ and $s_{r_2o}^{+b}$ are the non-radial slacks; v_i , u_{r_1} and z_{r_2} are the multipliers, corresponding to the i th input, the r_1 th desirable output and the r_2 th undesirable output, respectively; M is a large enough positive number; and b_j is the binary integer variable. As shown in model (5), the objective function inherits the concept of model (4) but attempts to minimize rather than maximize the sum of non-radial slacks with the L_1 norm. To ensure unit invariance, one possibility is to assign $1/x_{io}$, $1/y_{r_1o}^g$, $1/y_{r_2o}^b$ as the weights for the corresponding slacks in the objective function, i.e., $\sum_{i=1}^m s_{io}^-/x_{io} + \sum_{r_1=1}^{q_1} s_{r_1o}^{+g}/y_{r_1o}^g + \sum_{r_2=1}^{q_2} s_{r_2o}^{+b}/y_{r_2o}^b$ (Lovell and Pastor 1995; Pastor et al. 1999; Tone 2001). On the constraint side, $b_j^* = 0$ is embedded as a switch to determine whether DMU_j acts as a benchmark for DMU_o . If $b_j^* = 0$, then $d_j^* = 0$ and $\lambda_j^* > 0$, which implies that DMU_j belongs to hyperplane $-\sum_{i=1}^m v_i x_{ij} + \sum_{r_1=1}^{q_1} u_{r_1} y_{r_1j}^g - \sum_{r_2=1}^{q_2} z_{r_2} y_{r_2o}^b = 0$ and is the benchmark for DMU_o ; conversely, if $b_j^* = 1$, then $\lambda_j^* = 0$ and $d_j^* \geq 0$, which implies that DMU_j does not act as a benchmark for DMU_o . Moreover, by adding the constraint $\sum_{j=1}^n \lambda_j = 1$ and converting the fourth constraint into $-\sum_{i=1}^m v_i x_{ij} + \sum_{r_1=1}^{q_1} u_{r_1} y_{r_1j}^g - \sum_{r_2=1}^{q_2} z_{r_2} y_{r_2o}^b - \alpha + d_j = 0$, model (5) can be adapted to the case of VRS.

According to the optimal solution $(s_{io}^{*-}, s_{r_1o}^{+g*}, s_{r_2o}^{+b*})$ to model (5), the minimum distance-based efficiency δ_o^* for DMU_o can be formulated as follows (Cooper et al. 2007):

$$\delta_o^* = \frac{1 - \frac{1}{m} \sum_{i=1}^m s_{io}^{*-}/x_{io}}{1 + \frac{1}{q_1+q_2} \left(\sum_{r_1=1}^{q_1} s_{r_1o}^{+g*}/y_{r_1o}^g + \sum_{r_2=1}^{q_2} s_{r_2o}^{+b*}/y_{r_2o}^b \right)} \tag{6}$$

Here δ_o^* is considered as a composite measure ranging from 0 to 1 that indicates how each administrative region of the sampled data performs in terms of SD efficiency. An administrative region is SD efficient if and only if it holds $\delta_o^* = 1$, equivalently $(s_{io}^{*-}, s_{r_1o}^{+g*}, s_{r_2o}^{+b*}) = 0$.

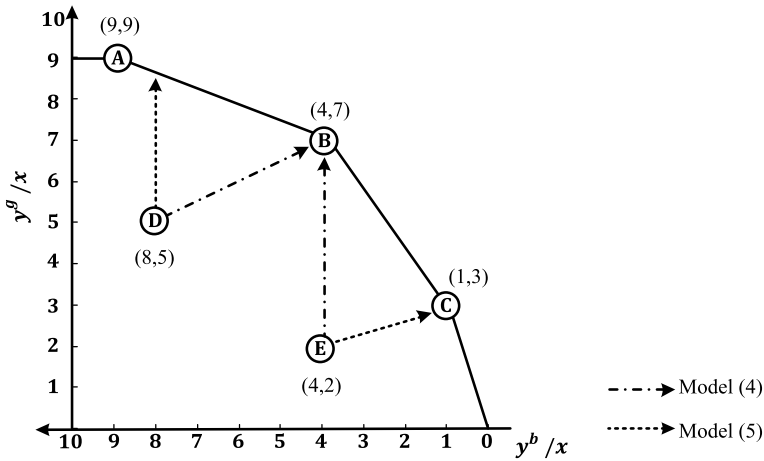


Fig. 1 The differences on benchmarking targets between models (4) and (5)

By contrast, an administrative region performs inefficiently when $\delta_o^* < 1$ and $(s_{io}^{-*}, s_{r1o}^{+g*}, s_{r2o}^{+b*}) \neq 0$.

In what follows, a simple example covering five DMUs, i.e., A, B, C, D and E, is applied to visualize the favorable specialty of the model (5). Each DMU uses one input x to produce two outputs, desirable y^g and undesirable y^b , where the amount of input x is unitized to 1 for simplicity. Figure 1 depicts the PPS spanned by these DMUs and shows the relevant results of models (4) and (5). It can be seen that DMUs A, B, C lie on the frontier; thus, they are efficient with optimal slacks $s_{r1o}^{+g*}, s_{r2o}^{+b*} = 0$, whereas the remaining two DMUs D and E are enveloped by the frontier, indicating that they are inefficient and have non-zero optimal slacks on s_{r2o}^{+b*} or s_{r1o}^{+g*} and should be further improved. If model (4) is used, for DMU D, the optimal slacks are $s_{r2o}^{+b*} = 4$ and $s_{r1o}^{+g*} = 2$; for DMU E, the optimal slacks are $s_{r2o}^{+b*} = 0$ and $s_{r1o}^{+g*} = 5$; DMU B (4,7) is determined as the benchmarking target. However, DMU B (4,7) is actually placed far from where the inefficient DMUs lie. Moreover, the proposed model (5) is competent to provide inefficient DMUs with more realistic benchmarking targets that are closer than those yielded by model (4). By using model (5), DMU D obtains optimal slacks $s_{r2o}^{+b*} = 0$ and $s_{r1o}^{+g*} = 3.6$, and DMU E obtains optimal slacks $s_{r2o}^{+b*} = 3$ and $s_{r1o}^{+g*} = 1$. The identified benchmarking targets of DMUs D and E are (8, 8.6) and (1, 3), respectively.

It should be noted that, in a similar fashion as explained above, incorporating undesirable outputs into other variants with different criteria is also feasible for generating the closest benchmarking targets. Based on the slacks-based measure, Wang et al. (2013a, b) put forward a linear bilevel programming problem (called mSBM) that takes the undesirable outputs into account. Moreover, An et al. (2015) incorporated the undesirable outputs into the conventional enhanced Russell measure, and then proposed its extension to obtain the minimum distance of a DMU_o to the efficient frontier. A similar study built on the additive measure has been made by Xiong et al. (2017), who determined the closest benchmarking targets in the presence of undesirable outputs by developing a closest target model that uses the weighted operator $1/(m + q_2)$ for input and undesirable output slacks and the weighted operator $1/q_1$ for desirable output slacks in the objective function. This model can be regarded as an extension under the framework of the additive measure, but its initial form

is not consistent with the standard additive model of Charnes et al. (1985) and it would not inherit the optimality of the mDD model of Aparicio et al. (2007) if only inputs and desirable outputs are considered. Regarding computation, such a way of embedding weighted operators in the objective function may also affect the optimality of slack variables.

Although the above models provide slightly different results, they are all conducive to globally lessening the differences between the values of the input, the desirable output and the undesirable output of the DMU_o and those of the benchmarking target. Despite the merit in generating the closest benchmarking targets, it should be noted that the aforementioned models perform the efficiency analysis in static situations only and can be further extended to accommodate time-varying data.

3.3 Window analysis for time-varying data

As efficiency varies with time, a general static analysis may be insufficient for time-dependent situations. The window analysis put forward by Charnes et al. (1984) is one of the most prevalent approaches for addressing cross sectional and longitudinal data (Wang et al. 2013a, b). It is not only useful for exploring the changes in efficiency of each DMU over time, but also helpful in enhancing the discriminatory power when cases with small sample sizes and a large number of variables occur (Ross and Droge 2002; Asmild et al. 2004; Sueyoshi et al. 2013).

This study combines the proposed model (5) with the window analysis procedure. Built on the notion of the moving average, window analysis treats each DMU in different periods as an independent unit, and divides time periods into a sequence of overlapping windows. Let us consider n DMUs over T periods, $t=1, \dots, T$, with window width w ($1 \leq w \leq T$). A total of $T - w + 1$ windows exist, and each window has $n \times w$ DMUs under evaluation of the model (5). The first window covers DMUs from periods $1, \dots, w$, the second window covers DMUs from periods $2, \dots, w + 1$, and so on. In this manner, each DMU in a period of a window can compare its own performance in other periods as well as the performance of other DMUs in the same and other periods.

4 Research sample and data collection

A total of 19 administrative regions in Taiwan, including 9 cities and 10 counties, over the period from 2011 to 2016 were sampled in this study. According to the Comprehensive Development Planning reported by the Council for Economic Planning and Development (CEPD), Executive Yuan, Taiwan, these cities and counties can be classified into four areas, namely, the northern, central, southern, and eastern areas. Figure 2 illustrates detailed information on the spatial distribution of these areas. The northern area consists of five cities, i.e., New Taipei, Taipei, Taoyuan, Hsinchu, and Keelung, and two counties, i.e., Yilan and Hsinchu. Taichung City and four counties, including Miaoli, Changhua, Yunlin, and Nantou, constitute the central area. The southern area is composed of Chiayi, Tainan and Kaohsiung cities as well as Chiayi and Pingtung counties. Hualien and Taitung counties group the eastern area.

The economic development and rapid industrialization of Taiwan heavily depends on the consumption of natural resources. However, Taiwan contains scarce indigenous natural

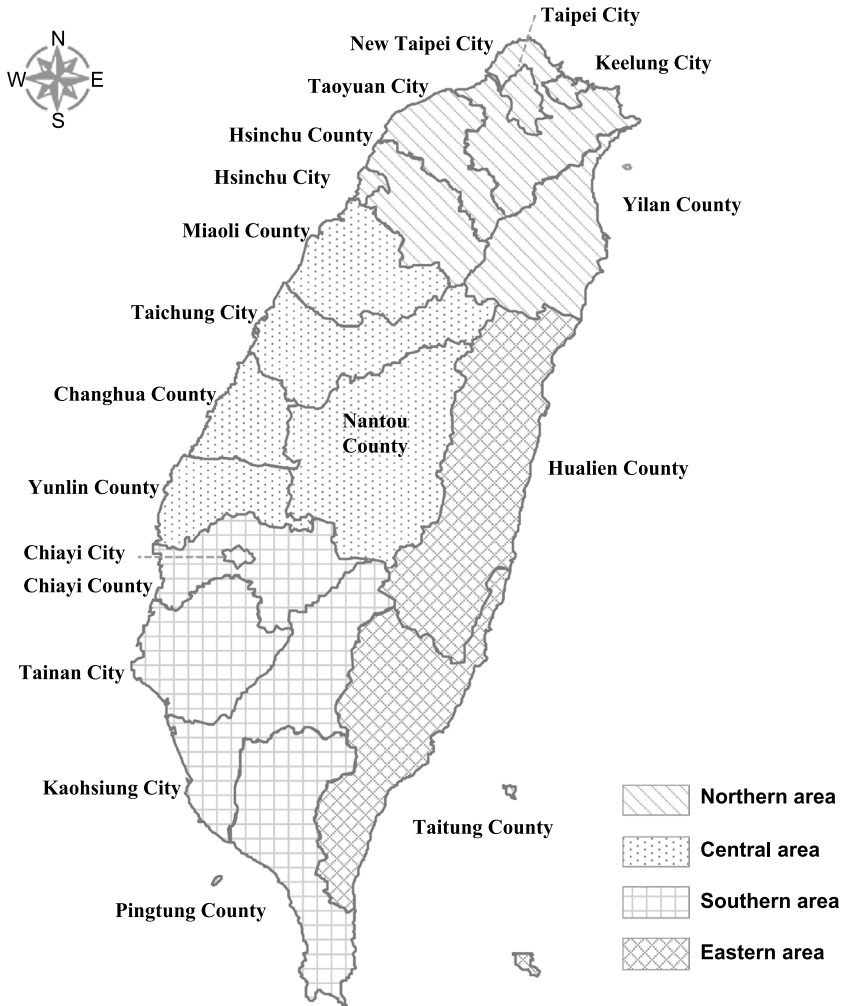
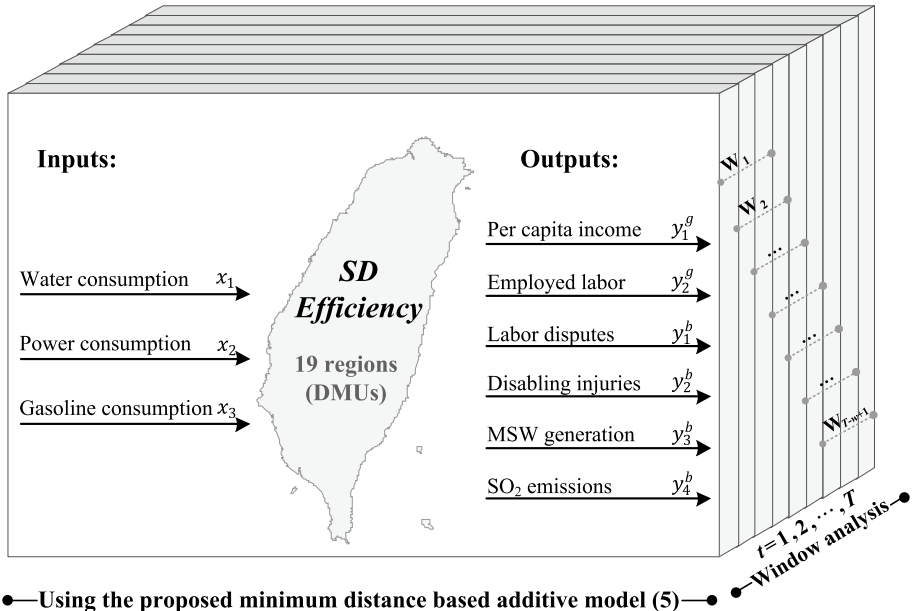


Fig. 2 Study area

resources. More than 98% of its energy resources, which are mostly in the form of fossil fuels including petroleum, coal, and natural gas, have long relied on foreign imports to supply the vast majority of energy needs. In addition, the shortage of water resources is another problem. Although Taiwan receives an average of approximately 2500 mm in annual rainfall, which is 2.5 times more than the world average, the average disposable water resource per capita from rainfall is approximately 4000 m³, which is less than one-fifth the world average. This scenario occurs because of the uneven spatiotemporal rainfall distribution and the dearth of storage capacity in short and steep river terrains. Therefore, in pursuit of economic development, Taiwan must effectively mitigate resource consumption and emphasise environmental protection and social welfare (CEPD 2004; NCSD 2009).

Each administrative region in Taiwan plays a crucial role in realizing sustainability at the regional scale. To explicitly assess SD efficiency across these administrative regions, three inputs, two desirable outputs and four undesirable outputs were adequately considered



●—Using the proposed minimum distance based additive model (5)—●

Fig. 3 Input-output data and research framework

in accordance with previous literature on SD issues. Figure 3 provides a clear view of the research framework and the input–output data selected in the present analysis. On the side of inputs, the annual amount of water consumption x_1 in million m^3 , the power consumption x_2 in Gigawatt hours (GWh) and the gasoline consumption x_3 in kiloliters (kL) are considered to directly reflect energy resources investment (Bruni et al. 2011; Yin et al. 2014; Yang et al. 2016). Regarding outputs, desirable outputs include per capita income y_1^g in thousands of NTD and the number of employed labor y_2^g per thousand persons, which represent the prosperity of regions under the economic dimension (Murias et al. 2006; Yin et al. 2014; Chen et al. 2017), whereas undesirable outputs are measured by the number of labor disputes y_1^b , the number of disabling injuries y_2^b , the amount of Municipal Solid Waste (MSW) generation y_3^b in tonnes and the amount of sulfur dioxide (SO_2) emissions y_4^b in parts per billion (ppb); among which the former two, y_1^b and y_2^b , reflect the burden on society (Shen et al. 2003; Miles and Munilla 2004; Iribarren et al. 2016), and the latter two, y_3^b and y_4^b , represent the degrees of environmental pollution in the waste and in the air, respectively (Hu 2006; Yin et al. 2014; Yu et al. 2017). The proposed model (5) is conducted with window analysis to perform a longitudinal efficiency evaluation for 19 administrative regions, $n=19$, with time period of 6 years, $T=6$. Given the consideration of the best balance of informativeness and stability of the efficiencies, a 3-year window width, $w=3$, is assumed (Charnes et al. 1994; Wang et al. 2013a, b). Thus, in the present analysis, there are four ($T-w+1=4$) overlapping windows proceeded for each administrative region, where each window covers a number of 76 ($n \times w=76$) observations.

The data for water consumption x_1 , power consumption x_2 and gasoline consumption x_3 were gathered from annual statistics documented by the Water Resources Agency, Taipower Company and Bureau of Energy; the per capita income y_1^g was collected from the Report on The Survey of Family Income and Expenditure of the Directorate-General of Budget, Accounting and Statistics (DGBAS); the employed labor y_2^g , labor disputes y_1^b and disabling injuries y_2^b were extracted from the Yearly Bulletin of Ministry of Labour; and

Table 1 Descriptive statistics of the input–output data

| Period | Statistics | Inputs | | | Desirable outputs | | | Undesirable outputs | | |
|--------|------------|-----------------------------|-----------------------------|--------------------------------|-----------------------------|--------------------------|--------------------------|------------------------------|--------------------------|-------------------------------------|
| | | Water consumption (x_1) | Power consumption (x_2) | Gasoline consumption (x_3) | Per capita income (y_1) | Employed labor (y_2) | Labor disputes (y_3) | Disabling injuries (y_4) | MSW generation (y_5) | SO ₂ emissions (y_6) |
| | | Million m ³ | GWh | kL | 1000 NTD | 1000 persons | No. | No. | Tonnes | ppb |
| 2016 | Mean | 766 | 11,145 | 782,225 | 606 | 591 | 1330 | 526 | 386,119 | 2.70 |
| | Max | 1910 | 29,966 | 2026,837 | 854 | 1947 | 4451 | 1823 | 990,138 | 4.51 |
| | Min | 41 | 941 | 160,524 | 499 | 105 | 59 | 26 | 88,339 | 1.29 |
| 2015 | SD | 485 | 10,391 | 633,322 | 90 | 543 | 1577 | 604 | 320,401 | 0.69 |
| | Mean | 766 | 10,829 | 760,010 | 592 | 587 | 1204 | 555 | 379,735 | 2.84 |
| | Max | 1759 | 29,088 | 1956,368 | 857 | 1945 | 4032 | 1859 | 940,086 | 4.38 |
| 2014 | Min | 39 | 919 | 155,687 | 486 | 104 | 35 | 23 | 77,094 | 1.35 |
| | SD | 510 | 10,057 | 616,616 | 100 | 541 | 1432 | 615 | 313,662 | 0.68 |
| | Mean | 829 | 10,801 | 742,362 | 599 | 581 | 1181 | 573 | 386,084 | 3.02 |
| 2013 | Max | 1959 | 29,277 | 1915,937 | 881 | 1927 | 4403 | 1856 | 1010,705 | 5.01 |
| | Min | 40 | 887 | 149,279 | 465 | 104 | 48 | 21 | 80,316 | 1.34 |
| | SD | 552 | 10,043 | 605,743 | 108 | 535 | 1452 | 609 | 326,666 | 0.84 |
| 2012 | Mean | 794 | 10,592 | 733,192 | 590 | 575 | 1245 | 562 | 388,924 | 3.03 |
| | Max | 1792 | 29,385 | 1885,241 | 866 | 1910 | 5226 | 1853 | 1067,465 | 5.23 |
| | Min | 41 | 852 | 143,903 | 470 | 104 | 61 | 26 | 79,276 | 1.30 |
| 2011 | SD | 502 | 9892 | 600,389 | 101 | 530 | 1569 | 605 | 330,099 | 0.90 |
| | Mean | 792 | 10,405 | 728,117 | 593 | 569 | 1207 | 570 | 389,977 | 2.89 |
| | Max | 1885 | 29,162 | 1858,334 | 871 | 1892 | 4114 | 1797 | 1111,862 | 5.30 |
| 2010 | Min | 42 | 843 | 144,158 | 476 | 103 | 89 | 25 | 79,511 | 1.30 |
| | SD | 507 | 9723 | 596,623 | 97 | 524 | 1436 | 595 | 337,535 | 0.93 |

Table 1 (continued)

| Period | Statistics | | Inputs | | | | Desirable outputs | | | Undesirable outputs | | | |
|--------|--------------------------------|--------------------------------|-----------------------------------|--------------------------------|-----------------------------|-----------------------------|---------------------------------|-----------------------------|--|---------------------|--|--|--|
| | Water consumption (x_1) | Power consumption (x_2) | Gasoline consumption (x_3) | Per capita income (y_1) | Employed labor (y_2) | Labor disputes (y_3) | Disabling injuries (y_4) | MSW generation (y_5) | SO ₂ emissions (y_6) | | | | |
| | Million m ³ | GWh | kL | 1000 NTD | 1000 persons | No. | No. | Tonnes | ppb | | | | |
| 2011 | Mean | 784 | 10,418 | 733,587 | 574 | 562 | 1179 | 574 | 390,708 | 3.32 | | | |
| | Max | 1708 | 28,947 | 1868,484 | 858 | 1853 | 4372 | 1813 | 1051,951 | 6.38 | | | |
| | Min | 41 | 853 | 151,223 | 454 | 104 | 100 | 25 | 76,047 | 1.80 | | | |
| | SD | 482 | 9678 | 601,539 | 106 | 513 | 1447 | 604 | 340,810 | 1.03 | | | |

the MSW generation y_3^b and the SO₂ emissions y_4^b were compiled from the Environment Resource Database of the Environmental Protection Administration. The descriptive statistics of the input–output data over 2011–2016 are summarized in Table 1.

5 Empirical Results and Discussions for Regional SD in Taiwan

The collected input–output dataset was analysed under the presented research framework, and the resulting SD efficiency for 19 administrative regions of Taiwan from 2011 to 2016 are reported in Table 2, where the annual SD efficiency is the average of the four overlapping 3-year windows using the window analysis procedure: 2011–2013, 2012–2014, 2013–2015, and 2014–2016. The results show that during all time periods, four administrative regions, New Taipei City, Yunlin County, Taitung County, and Chiayi City, were consistently efficient and received a SD efficiency of $\delta_o^* = 1$. These four regions could serve as benchmarks for other regions with an SD efficiency of $\delta_o^* < 1$ because they perform efficiently in consuming input resources of water x_1 , power x_2 , and gasoline x_3 to produce economical outputs of per capita income y_1^g and employed labor y_2^g while restraining the social burden of labor disputes y_1^b and disabling injuries y_2^b as well as the environmental pollution of MSW generation y_3^b and SO₂ emissions y_4^b . For most of the periods, Taipei City, Nantou County, Chiayi County, and Keelung City were deemed as SD efficient, and they all gained an average SD efficiency over 0.990. It can be also observed that three administrative regions, Taoyuan City, Tainan City, and Hualien County, presented significant improvements in SD efficiency from 2011 to 2013, whereas their SD efficiency dropped after 2014.

Table 2 Annual score of SD efficiency for 19 administrative regions

| Administrative region | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | Average |
|-----------------------|--------|--------|--------|--------|--------|--------|---------|
| New Taipei City | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Taipei City | 0.9500 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.9917 |
| Taoyuan City | 0.6379 | 0.7423 | 0.7650 | 0.7847 | 0.6812 | 0.7136 | 0.7208 |
| Taichung City | 0.5922 | 0.4956 | 0.5692 | 0.5533 | 0.4693 | 0.4380 | 0.5196 |
| Tainan City | 0.7140 | 0.8332 | 0.8605 | 1.0000 | 0.7757 | 0.7169 | 0.8167 |
| Kaohsiung City | 0.7085 | 0.8196 | 0.7741 | 0.7914 | 0.7593 | 0.6791 | 0.7553 |
| Yilan County | 0.9598 | 1.0000 | 0.9515 | 0.9056 | 0.9066 | 0.8550 | 0.9298 |
| Hsinchu County | 1.0000 | 0.8630 | 0.8306 | 0.8096 | 0.7827 | 0.6814 | 0.8279 |
| Miaoli County | 1.0000 | 1.0000 | 1.0000 | 0.9331 | 0.8833 | 0.9037 | 0.9533 |
| Changhua County | 0.9442 | 1.0000 | 0.9844 | 1.0000 | 0.9536 | 0.9552 | 0.9729 |
| Nantou County | 1.0000 | 1.0000 | 0.9939 | 1.0000 | 1.0000 | 1.0000 | 0.9990 |
| Yunlin County | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Chiayi County | 1.0000 | 1.0000 | 0.9459 | 1.0000 | 1.0000 | 1.0000 | 0.9910 |
| Pingtung County | 0.9093 | 0.9564 | 0.9827 | 0.9621 | 1.0000 | 1.0000 | 0.9684 |
| Taitung County | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Hualien County | 0.9069 | 1.0000 | 1.0000 | 0.8897 | 0.7838 | 0.7898 | 0.8950 |
| Keelung City | 1.0000 | 1.0000 | 1.0000 | 0.9700 | 1.0000 | 1.0000 | 0.9950 |
| Hsinchu City | 0.8869 | 0.9094 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.9660 |
| Chiayi City | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |

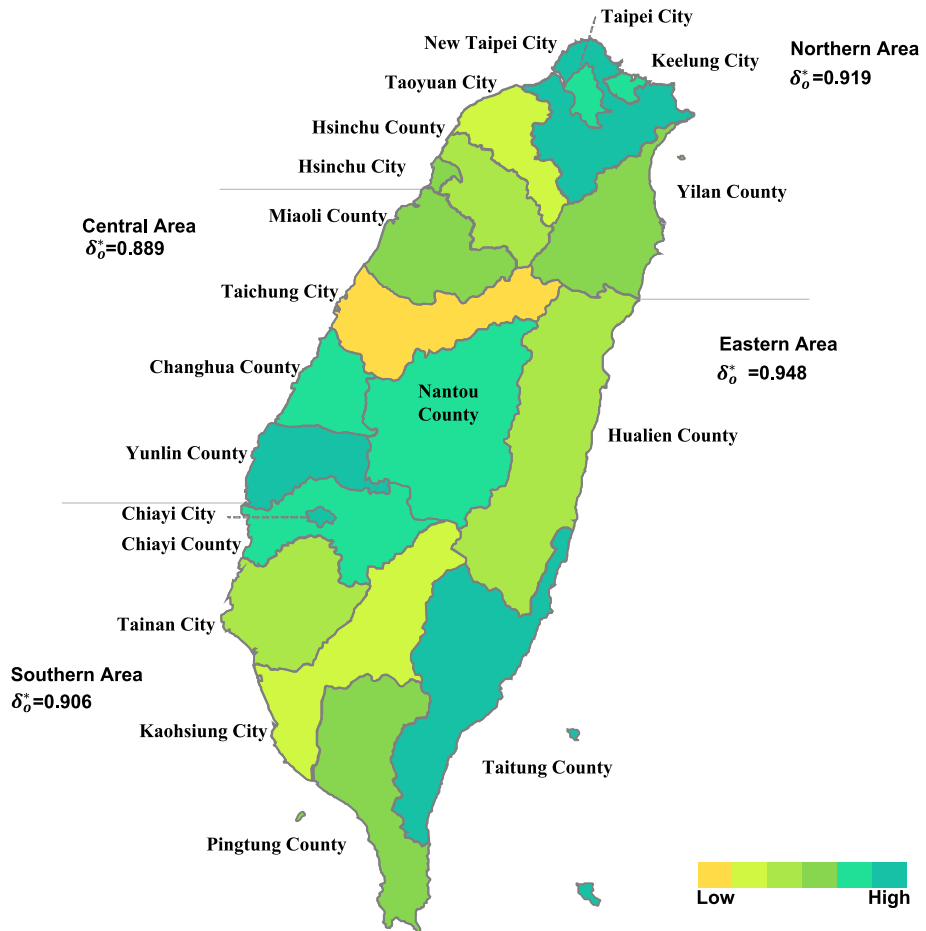


Fig. 4 Spatial distribution of the SD efficiency for 19 administrative regions

Kaohsiung City and Changhua County show a fluctuating SD efficiency over the research periods.

The average annual SD efficiencies of 19 administrative regions within four areas are depicted in Fig. 4 which provides an overview of the spatial distribution of Taiwanese SD efficiency. As is shown, among the northern area regions, Taoyuan City and Hsinchu County fall in the bottom two places with an average SD efficiency lower than 0.850. In the central area, four out of five regions perform efficiently and present average SD efficiencies above 0.950, whereas Taichung City is the least efficient with an average SD efficiency that is far lower than the others. In the southern area, Chiayi City takes first place with the top SD efficiency of 1.000, and it is followed by Chiayi County with average SD efficiency of 0.991. Kaohsiung City comes last in this area and obtains an average SD efficiency of only 0.755. Moreover, in the eastern area, Hualien County is not efficient enough and its average SD efficiency is less than 0.900. Notably, the efficient state for the regions implies that the well balanced development among the three pillars of sustainability was achieved, while the inefficient state indicates that some improvements must be made by

Table 3 Average optimal slacks of inputs and outputs for 19 administrative regions

| Administrative region | Inputs | | | Desirable outputs | | | Undesirable outputs | | | |
|-----------------------|-----------------------------|-----------------------------|--------------------------------|---------------------------------|------------------------------|----------|------------------------------|----------------------------------|------------------------------|---|
| | Water consumption (s_1^-) | Power consumption (s_2^-) | Gasoline consumption (s_3^-) | Per capita income (s_1^{+b*}) | Employed labor (s_2^{+b*}) | | Labor disputes (s_1^{+b*}) | Disabling injuries (s_2^{+b*}) | MSW generation (s_3^{+b*}) | SO ₂ emissions (s_4^{+b*}) |
| New Taipei City | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Taipei City | 0 | 104.548 | 0 | 0 | 0 | 0 | 0 | 8.000 | 24,455.760 | 0.026 |
| Taoyuan City | 13.577 | 8134.941 | 252,934.106 | 0 | 253.482 | 539.989 | 539.989 | 843.033 | 35,014.565 | 0.292 |
| Taichung City | 1103.693 | 10,107.139 | 632,903.197 | 0 | 81.557 | 102.237 | 102.237 | 323.644 | 20,732.731 | 0.070 |
| Tainan City | 8.930 | 7715.570 | 152,420.790 | 0 | 28.004 | 27.202 | 27.202 | 133.496 | 32,486.536 | 0.175 |
| Kaohsiung City | 59.070 | 7894.535 | 135,415.362 | 5.887 | 85.879 | 1264.657 | 1264.657 | 33.320 | 126,963.248 | 1.376 |
| Yilan County | 0 | 142.074 | 26,909.577 | 0 | 4.624 | 29.166 | 29.166 | 5.368 | 8265.438 | 0.007 |
| Hsinchu County | 0 | 640.858 | 130,032.588 | 0 | 0.361 | 74.209 | 74.209 | 70.177 | 686.123 | 0.161 |
| Miaoli County | 0 | 186.334 | 43,238.291 | 0 | 0 | 3.256 | 3.256 | 4.153 | 989.688 | 0.029 |
| Changhua County | 2.812 | 178.435 | 17,046.752 | 1.425 | 0.615 | 0.442 | 0.442 | 2.718 | 12,321.758 | 0.179 |
| Nantou County | 0 | 0 | 600.972 | 0.067 | 0 | 0 | 0 | 0.427 | 28.453 | 0 |
| Yunlin County | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Chiayi County | 0 | 0.373 | 4022.477 | 0 | 0.096 | 0 | 0 | 0 | 3206.479 | 0.053 |
| Pingtung County | 8.094 | 101.592 | 21,875.698 | 17.386 | 0.654 | 0 | 0 | 0.322 | 1464.569 | 0.029 |
| Taitung County | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Hualien County | 210.689 | 15.191 | 21,984.308 | 0 | 0.413 | 19.617 | 19.617 | 0.506 | 744.967 | 0.098 |
| Keelung City | 0 | 0 | 284.061 | 0.192 | 0 | 0 | 0 | 2.040 | 114.826 | 0.027 |
| Hsinchu City | 0 | 643.135 | 989.248 | 0 | 0 | 9.480 | 9.480 | 2.721 | 1071.600 | 0.059 |
| Chiayi City | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

less efficient regions, from the efficiency perspective. Table 3 presents the average optimal slacks for each input and output using the proposed model (5). These non-zero optimal slacks clearly manifest the sources resulting in inefficiency and indicate the proper decreases of the corresponding inputs and undesirable outputs as well as the increases of the corresponding desirable outputs based on the minimum distance notion. That is to say, adjusting these slacks would be conducive to a better SD performance and less efficient regions can use this information as a reference to draw up effective policies and strategies for SD improvement. Taking Taoyuan City ($\delta_o^* = 0.7208$) as an example, it has the non-zero optimal slacks of s_1^{-*} , s_2^{-*} , s_3^{-*} , s_2^{+g*} , s_1^{+b*} , s_2^{+b*} , s_3^{+b*} , and s_4^{+b*} . This finding indicates that to become efficient, Taoyuan City could decrease water, power, and gasoline consumption by 13.577 million m³, 8134.941 GWh, and 252,934.106 kL, respectively; expand the number of employed labor by 253.482 thousand persons; and reduce the number of labor disputes, disabling injuries, MSW generation, and SO₂ emissions by 540, 843, 35,014.565 tonnes, and 0.292 ppb, respectively. Furthermore, regarding Taichung City, which achieves the lowest average SD efficiency ($\delta_o^* = 0.5196$), the optimal slacks information reveals that it has resource input excesses for water ($s_1^{-*} = 1103.693$), power ($s_2^{-*} = 10,107.139$) and gasoline ($s_3^{-*} = 632,903.197$); output shortages for employed labor ($s_2^{+g*} = 81.557$); and output overproduction for labor disputes ($s_1^{+b*} = 102$), disabling injuries ($s_2^{+b*} = 324$), MSW generation ($s_3^{+b*} = 20,732.731$) and SO₂ emissions ($s_4^{+b*} = 0.07$). Therefore, more specific policies and effective activities should be particularly devised by Taichung government to manage those inefficient sources.

Figure 4 also shows that among the four areas, the eastern area is ahead of the others in terms of average SD efficiency. In fact, due to the large coverage of mountain terrain, this area is less developed and has a very low population density. Although the eastern area is not impressive economically, it has cut a figure in resources saving and ecological conservation. With regard to areas in the western coastal plain where the majority

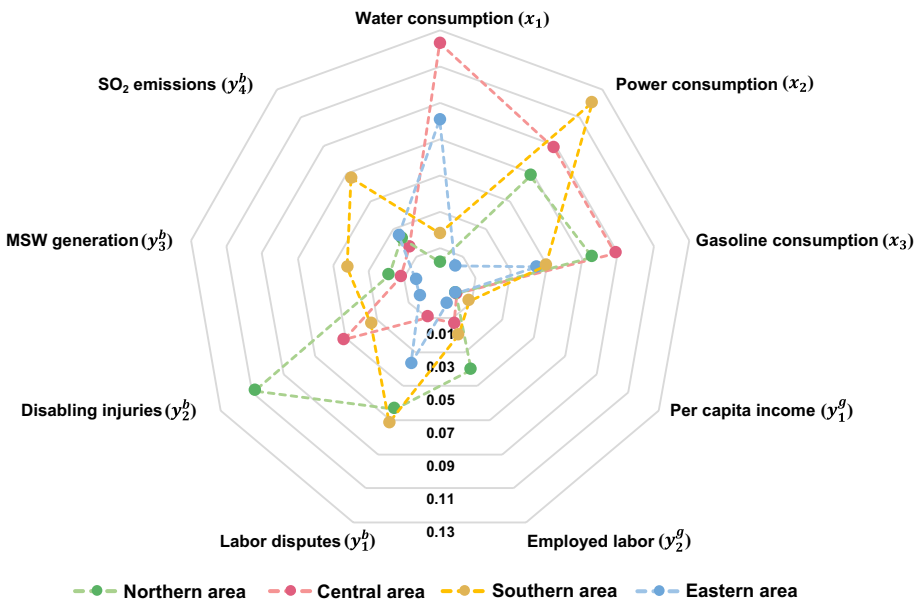


Fig. 5 Average potential improvement for the four areas in Taiwan

of the population resides, the northern area achieves the highest average SD efficiency ($\delta_o^* = 0.919$), followed by the southern area ($\delta_o^* = 0.906$) and the central area ($\delta_o^* = 0.889$). Figure 5 illustrates the average potential improvement of each input and output among the four areas, which is expressed as the ratio of optimal slack to original value. As shown, for the northern area, disabling injuries y_2^b and gasoline consumption x_3 are primary loadings affecting SD and must be reduced on average by 10.82% and 7.56%, respectively. For the southern area, power consumption x_2 (12.09%), labor disputes y_1^b (7.16%) and SO_2 emissions y_4^b (6.64%) are the top three priorities for improving SD efficiency. Furthermore, the central area has the highest room for improvement in water consumption x_1 , which should be decreased by 12.30% on average. These results may indicate that inefficient sources vary from area to area, most likely due to differences in industry structures. The northern area has a mature development of business services and is vigorously high-tech concentrated. The integrated circuits (IC) industry, computer and peripherals industry, optoelectronics industry, biotechnology industry, and telecommunications industry present industrial centres in this area, and they are mostly incubated at Hsinchu Science Park and Nankang Software Park. The labor intensive productions of these industries involve numerous underlying hazards at the workplace that therefore cause occupational injuries and illnesses. Local governments in the northern area could pressure the industries to comply with labour safety and health standards or guidelines documented in the Electronic Industry Code of Conduct (EICC), Occupational Health and Safety Assessment Series 18,001 (OHSAS 18,001), and Social Accountability 8000 (SA 8000), thereby lessening the social burden (Lo et al. 2014; Santos et al. 2018; Tuzek et al. 2018). The central area hosts the precision machinery industry and traditional industries of textiles, clothing, footwear and floriculture. With the completion of the Taichung Science Park and the rapid growth of required industrial water, the problem of water resource scarcity is getting serious in central Taiwan. The Water Resources Agency also reports that the central area might have a shortage of water supply of approximately 170,000 tonnes per day over the next decade. To eliminate the dependency on water resources, technologies associated with waste water recovery and reuse as well as effective water management practices must be incorporated into operational strategies of water-intensive industries (Angelakis et al. 2003; Chu et al. 2004; Vajnhandl and Valh 2014). Meanwhile, a series of policies and actions should be continuously promoted by local governments to deepen the awareness of water resources conservation. In the southern area, there is a great concentration of heavy industries including the petrochemical industry, steel industry, electric power industry, and naval architecture industry, which could explain why the southern area suffers the most pressure from energy consumption and air pollution. Therefore, there is a rising need for these power-hungry industries to optimize the energy usage of their operations. Appropriate policies, such as electricity pricing reform and regulatory requirement on certain share of renewable energy, including solar, wind, and hydraulic, could be further implemented to not only force energy-saving activities but also accelerate the development of renewable energy (Liming et al. 2008; Kohler 2014; Lin et al. 2017).

Figure 6 illustrates the annual SD efficiencies for the four areas individually and for Taiwan as a whole from 2011 to 2016 to demonstrate the changes in efficiency during the research periods from a dynamic perspective. As shown, the SD efficiency of the southern area rose dramatically from 2011 to 2014 and it even surpasses that of the eastern area in 2014. This uptrend is contributed by the progress on SD efficiency in Tainan City, Kaohsiung City, and Pingtung County. A similar but slight change appears in the efficiency of the northern area from 2011–2013. Three out of seven administrative regions, i.e., Taipei City, Hsinchu City, and Taoyuan City, achieved improvement in

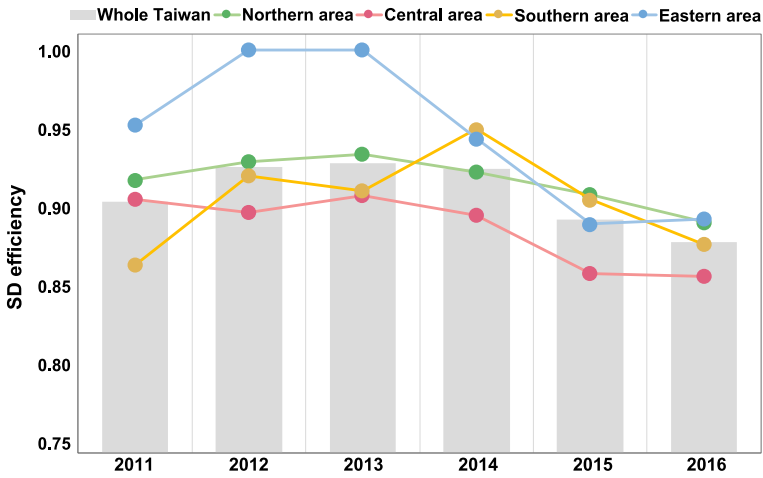


Fig. 6 Average SD efficiency trend for four areas and whole Taiwan

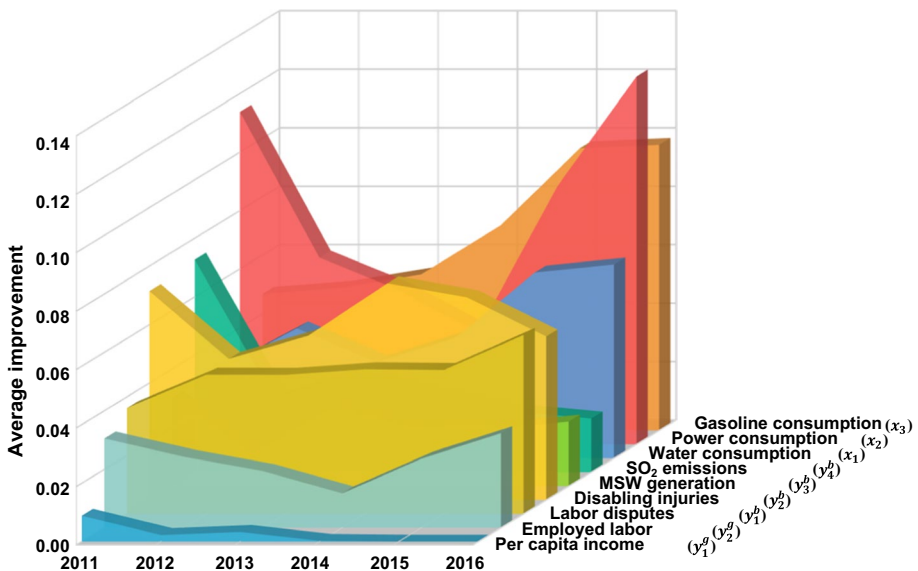


Fig. 7 The trend of average improvement of inputs and outputs for whole Taiwan

their SD efficiencies over the first 3 years, which resulted in the slow upward efficiency trend for the northern area. However, all the areas show had an evident downswing in efficiency over the last 3 years. The SD efficiency of Taiwan (grey bar in Fig. 6) has declined since 2014 and even dropped to a performance level worse than in 2011 for the 2015–2016 period. This finding implies that although Taiwan has been attempting to meet SD goals, it still has a long way to go before it can realize ideal sustainability. To remedy the worsening trend of SD efficiency, Taiwan must accelerate SD improvement

and intensify the balance of resource consumption, economic prosperity, environmental protection, and social welfare by dispelling the sources that deteriorate SD efficiency. The annual potential improvement of inputs and outputs of Taiwan is shown in Fig. 7. This figure provides policymakers with holistic insights on changes in the magnitudes of inputs and outputs, which could be adjusted during varying periods to enable them to draw up precisely relevant policies for SD improvement. The required improvement of per capita income y_1^g has gradually decreased and its magnitude is much less than that of others, indicating that pressure to enrich inhabitants has become weaker in general. Furthermore, there appears to be an evident magnitude of potential improvements for power consumption x_2 , disabling injuries y_2^b , and SO₂ emissions y_4^b , and a rising trend in required improvements is observed for water consumption x_1 , gasoline consumption x_3 and the labor disputes y_1^b . These findings imply that these variables serve critical roles in promoting SD, and striving to eliminate the inefficiencies of which would be more conducive for improving Taiwanese SD performance. Therefore, Taiwan must place greater emphasis on resource conservation, environment protection and social welfare instead of merely pursuing economic prosperity.

6 Concluding Remarks

Along with the wave of sustainability sweeping the world in the past few decades, progressing towards regional SD has become a matter of concern for improving societal well-being and quality of life. Benchmarking and performance evaluation has gained widespread acceptance as a scientific process to follow up and accelerate regional SD. In this study, a novel additive DEA model with the consideration of undesirable outputs is proposed based on the minimum distance measure, which can not only construct a composite efficiency indicator but also provide holistic insights into improved strategies according to closest benchmarking target notion. The window analysis was then employed to successfully perform the work of cross-sectional and longitudinal efficiency evaluations.

Using an empirical dataset encompassing three inputs, two desirable outputs, and four undesirable outputs, such an assessment framework is applied to benchmark SD efficiency across 19 administrative regions of Taiwan for the period from 2011 to 2016. The study also elaborates how each administrative region performs in SD, explores which major sources lead to inefficiency and discusses some potential policies that contribute towards sustainability. The empirical results reveal that the sources of inefficiency may vary with industrial structure. In general, the administrative regions in the northern, central and southern areas faced relatively higher room for improvement to disabling injuries, water consumption and power consumption, respectively. The study also found that for the recent 3 years, Taiwan as a whole experienced deterioration in terms of average SD efficiency, implying that the pressure for SD improvement has become more intense. These findings provide local governments with valuable information for devising corresponding policies and regulations that facilitate a more sustainable society.

This study brings a two-fold contribution, both methodological and empirical, to the existing literature. First, this study presents a novel extension in non-radial DEA in which the minimum distance-based additive model is extended to accommodate undesirable outputs and conjoined with window analysis. The newly developed model preserves the desirable feature of standard additive model in meeting Pareto–Koopmans optimality for efficient DMUs but owns the merit of determining convincing benchmarking targets and a

more feasible direction for improving inefficient DMUs. Remarkably, the proposed model is promising for a wide range of practical applications, especially to those with undesirable outputs. In order to accelerate progress in achieving SD, other regions or countries can implement this model to examine their SD performance with a dynamic view and thereby draft effective policies for SD improvement. Furthermore, this study conducts a holistic investigation into sustainability and responds to the need for compositing a reliable indicator of SD efficiency at the regional level, whereas previous studies mainly dealt with economic and environmental problems and rarely focused on social impacts. This topic conforms to the contemporary trend of sustainability, and the findings of this study could contribute to the literature on regional SD promotion.

There remain a few limitations that should be clarified. Regarding time-dependent benchmarking, the use of window analysis fails to offer precise benchmarking information that indicates the change in efficiency of an evaluated region between two adjacent periods of time by examining the pre- and post-values of input, desirable and undesirable outputs. The Malmquist index analysis presented by Malmquist (1953) is an effective approach for addressing this limitation. Future researches could attempt to extend the proposed model to include the Malmquist index to take a closer look at the pairwise changes in SD performance. Moreover, in the empirical application to Taiwan SD, only one desirable output of the observed variables is expressed in per capita term, implying that conceptual asymmetry might appear in the input–output data set. Using GDP in place of per capita income would be desirable but difficult due to data availability issue in Taiwan (DGBAS 2012). The other alternative could be using the product of the per capita income and the number of inhabitants of a region. Additionally, this study does not allow for the environmental variables (also called non-controllable variables), such as population and land area, which are exogenously fixed but can affect the benchmarking results to a certain extent (Banker and Morey 1986; Zhu 1996). A noteworthy topic for future research would be to extend the proposed model by considering this kind of variable so as to bring more insights into SD improvements. Finally, one should note that the Benefit of Doubt model, presented by Melyn and Moesen (1991) and introduced at length by Cherchye et al. (2007), is also a useful and credible DEA-based approach for creating composite indicators. However, it mainly deals with the flexibility issue of weighting sub-indicators and does not consider the input and output slacks. Thus, the proposed model still remains advantageous and applicable to benchmarking issues due to its capacity to provide insights into the sources of inefficiency and the strategies of performance improvement.

References

- Ali, A. I., & Seiford, L. M. (1990). Translation invariance in data envelopment analysis. *Operations Research Letters*, 9(6), 403–405.
- An, Q., Pang, Z., Chen, H., & Liang, L. (2015). Closest targets in environmental efficiency evaluation based on enhanced Russell measure. *Ecological Indicators*, 51, 59–66.
- Angelakis, A. N., Bontoux, L., & Lazarova, V. (2003). Challenges and perspectives for water recycling and reuse in EU countries. *Water Science and Technology: Water Supply*, 3(4), 59–68.
- Aparicio, J., Ruiz, J. L., & Sirvent, I. (2007). Closest targets and minimum distance to the Pareto-efficient frontier in DEA. *Journal of Productivity Analysis*, 28(3), 209–218.
- Asmild, M., Paradi, J. C., Aggarwall, V., & Schaffnit, C. (2004). Combining DEA window analysis with the Malmquist index approach in a study of the Canadian banking industry. *Journal of Productivity Analysis*, 21(1), 67–89.

- Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9), 1078–1092.
- Banker, R. D., & Morey, R. C. (1986). Efficiency analysis for exogenously fixed inputs and outputs. *Operations Research*, 34(4), 513–521.
- Belu, C. (2009). Ranking corporations based on sustainable and socially responsible practices. A data envelopment analysis (DEA) approach. *Sustainable Development*, 17(4), 257–268.
- Bruni, M. E., Guerriero, F., & Patitucci, V. (2011). Benchmarking sustainable development via data envelopment analysis: An Italian case study. *International Journal of Environmental Research*, 5(1), 47–56.
- Caiado, R. G. G., de Freitas Dias, R., Mattos, L. V., Quelhas, O. L. G., & Leal Filho, W. (2017). Towards sustainable development through the perspective of eco-efficiency: A systematic literature review. *Journal of Cleaner Production*, 165(1), 890–904.
- Carboni, O. A., & Russu, P. (2015). Assessing regional wellbeing in Italy: An application of Malmquist-DEA and self-organizing map neural clustering. *Social Indicators Research*, 122(3), 677–700.
- CEPD (The Council for Economic Planning and Development). (2004). *Taiwan agenda 21: Vision and strategies for national sustainable development*. Taiwan: CEPD.
- Chambers, R. G., Chung, Y., & Färe, R. (1996). Benefit and distance functions. *Journal of Economic Theory*, 70(2), 407–419.
- Charmondusit, K., Phatarachaisakul, S., & Prasertpong, P. (2014). The quantitative eco-efficiency measurement for small and medium enterprise: A case study of wooden toy industry. *Clean Technologies and Environmental Policy*, 16(5), 935–945.
- Charnes, A., Clark, C. T., Cooper, W. W., & Golany, B. (1984). A developmental study of data envelopment analysis in measuring the efficiency of maintenance units in the US air forces. *Annals of Operations Research*, 2(1), 95–112.
- Charnes, A., Cooper, W. W., Golany, B., Seiford, L., & Stutz, J. (1985). Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. *Journal of Econometrics*, 30(1), 91–107.
- Charnes, A., Cooper, W. W., Lewin, A. Y., & Seiford, L. M. (1994). *Data envelopment analysis: Theory, methodology, and application*. Norwell: Kluwer Academic Publishers.
- Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429–444.
- Charnes, A., Cooper, W. W., & Thrall, R. M. (1986). Classifying and characterizing efficiencies and inefficiencies in data development analysis. *Operations Research Letters*, 5(3), 105–110.
- Charnes, A., Cooper, W. W., & Thrall, R. M. (1991). A structure for classifying and characterizing efficiency and inefficiency in data envelopment analysis. *Journal of Productivity Analysis*, 2(3), 197–237.
- Chen, L., Wang, Y., Lai, F., & Feng, F. (2017). An investment analysis for China's sustainable development based on inverse data envelopment analysis. *Journal of Cleaner Production*, 142(4), 1638–1649.
- Cherchye, L., Moesen, W., Rogge, N., & Van Puyenbroeck, T. (2007). An introduction to 'benefit of the doubt' composite indicators. *Social Indicators Research*, 82(1), 111–145.
- Chu, J., Chen, J., Wang, C., & Fu, P. (2004). Wastewater reuse potential analysis: Implications for China's water resources management. *Water Research*, 38(11), 2746–2756.
- Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management*, 51(3), 229–240.
- Cooper, W. W., Park, K. S., & Pastor, J. T. (1999). RAM: A range adjusted measure of inefficiency for use with additive models, and relations to other models and measures in DEA. *Journal of Productivity Analysis*, 11(1), 5–42.
- Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software* (2nd ed.). New York: Springer.
- DGBAS (Directorate-General of Budget, Accounting and Statistics) (2012). <https://www.dgbas.gov.tw/ct.asp?xItem=31080&ctNode=5686&mp=1>. Released 1 May 2012.
- Du, J., Liang, L., & Zhu, J. (2010). A slacks-based measure of super-efficiency in data envelopment analysis: A comment. *European Journal of Operational Research*, 204(3), 694–697.
- Elkington, J. (1998). Partnerships from cannibals with forks: The triple bottom line of 21st-century business. *Environmental Quality Management*, 8(1), 37–51.
- Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General)*, 120(3), 253–290.
- Gibbs, D. (1998). Regional development agencies and sustainable development. *Regional Studies*, 32(4), 365–368.
- Golany, B., & Roll, Y. (1989). An application procedure for DEA. *Omega*, 17(3), 237–250.

- Gómez-Calvet, R., Gómez-Calvet, A. R., Conesa, D., & Tortosa-Ausina, E. (2016). On the dynamics of eco-efficiency performance in the European Union. *Computers & Operations Research*, *66*, 336–350.
- González, E., Cárcaba, A., & Ventura, J. (2011). The importance of the geographic level of analysis in the assessment of the quality of life: The case of Spain. *Social Indicators Research*, *102*(2), 209–228.
- Hailu, A., & Veeman, T. S. (2001). Non-parametric productivity analysis with undesirable outputs: An application to the Canadian pulp and paper industry. *American Journal of Agricultural Economics*, *83*(3), 605–616.
- Herrera-Ulloa, Á. F., Charles, A. T., Lluch-Cota, S. E., Ramirez-Aguirre, H., Hernández-Vázquez, S., & Ortega-Rubio, A. (2003). A regional-scale sustainable development index: The case of baja california sur, mexico. *International Journal of Sustainable Development and World Ecology*, *10*(4), 353–360.
- Holling, C. S. (2001). Understanding the complexity of economic, ecological, and social systems. *Ecosystems*, *4*(5), 390–405.
- Hu, J. L. (2006). Efficient air pollution abatement for regions in China. *International Journal of Sustainable Development and World Ecology*, *13*(4), 327–340.
- Iribarren, D., Martín-Gamboa, M., O'Mahony, T., & Dufour, J. (2016). Screening of socio-economic indicators for sustainability assessment: A combined life cycle assessment and data envelopment analysis approach. *The International Journal of Life Cycle Assessment*, *21*(2), 202–214.
- Jollands, N., Lermitt, J., & Patterson, M. (2004). Aggregate eco-efficiency indices for New Zealand—A principal components analysis. *Journal of Environmental Management*, *73*(4), 293–305.
- Kohler, M. (2014). Differential electricity pricing and energy efficiency in South Africa. *Energy*, *64*(1), 524–532.
- Lebel, L., Anderies, J. M., Campbell, B., Folke, C., Hatfield-Dodds, S., Hughes, T. P., et al. (2006). Governance and the capacity to manage resilience in regional social-ecological systems. *Ecology and Society*, *11*(1), 19.
- Lee, K., & Farzipoor Saen, R. (2012). Measuring corporate sustainability management: A data envelopment analysis approach. *International Journal of Production Economics*, *140*(1), 219–226.
- Liming, H., Haque, E., & Barg, S. (2008). Public policy discourse, planning and measures toward sustainable energy strategies in Canada. *Renewable and Sustainable Energy Reviews*, *12*(1), 91–115.
- Lin, H., Wang, Q., Wang, Y., Liu, Y., Sun, Q., & Wennersten, R. (2017). The energy-saving potential of an office under different pricing mechanisms: Application of an agent-based model. *Applied Energy*, *202*(15), 248–258.
- Liu, Y., Wang, W., Li, X., & Zhang, G. (2010). Eco-efficiency of urban material metabolism: A case study in Xiamen, China. *International Journal of Sustainable Development and World Ecology*, *17*(2), 142–148.
- Lo, C. K., Pagell, M., Fan, D., Wiengarten, F., & Yeung, A. C. (2014). OHSAS 18001 certification and operating performance: The role of complexity and coupling. *Journal of Operations Management*, *32*(5), 268–280.
- Lovell, C. K., & Pastor, J. T. (1995). Units invariant and translation invariant DEA models. *Operations Research Letters*, *18*(3), 147–151.
- Lovell, C. K., Pastor, J. T., & Turner, J. A. (1995). Measuring macroeconomic performance in the OECD: A comparison of European and non-European countries. *European Journal of Operational Research*, *87*(3), 507–518.
- Lozano, S., & Gutierrez, E. (2008). Non-parametric frontier approach to modelling the relationships among population, GDP, energy consumption and CO₂ emissions. *Ecological Economics*, *66*(4), 687–699.
- Mahdiloo, M., Saen, R. F., & Lee, K. (2015). Technical, environmental and eco-efficiency measurement for supplier selection: An extension and application of data envelopment analysis. *International Journal of Production Economics*, *168*, 279–289.
- Mahlberg, B., & Sahoo, B. K. (2011). Radial and non-radial decompositions of Luenberger productivity indicator with an illustrative application. *International Journal of Production Economics*, *131*(2), 721–726.
- Malmquist, S. (1953). Index numbers and indifference surfaces. *Trabajos de estadística*, *4*(2), 209–242.
- Melyn, W., & Moesen, W. (1991). Towards a synthetic indicator of macroeconomic performance: Unequal weighting when limited information is available. *Public Economics Research Paper 17*, CES, KU Leuven.
- Michelsen, O., Fet, A. M., & Dahlsrud, A. (2006). Eco-efficiency in extended supply chains: A case study of furniture production. *Journal of Environmental Management*, *79*(3), 290–297.
- Miles, M. P., & Munilla, L. S. (2004). The potential impact of social accountability certification on marketing: A short note. *Journal of Business Ethics*, *50*(1), 1–11.

- Murias, P., Martinez, F., & De Miguel, C. (2006). An economic wellbeing index for the Spanish provinces: A data envelopment analysis approach. *Social Indicators Research*, 77(3), 395–417.
- NCSO (National Council for Sustainable Development) (2009). *Sustainable development policy guidelines*. <https://nsdn.epa.gov.tw/>. Accessed 30 July 2017.
- Nissi, E., & Sarra, A. (2018). A measure of well-being across the Italian urban areas: An integrated DEA-entropy approach. *Social Indicators Research*, 136(3), 1183–1209.
- Pastor, J. T., Ruiz, J. L., & Sirvent, I. (1999). An enhanced DEA Russell graph efficiency measure. *European Journal of Operational Research*, 115(3), 596–607.
- Rashidi, K., & Farzipoor Saen, R. (2015). Measuring eco-efficiency based on green indicators and potentials in energy saving and undesirable output abatement. *Energy Economics*, 50, 18–26.
- Reinhard, S., Lovell, C. K., & Thijssen, G. (1999). Econometric estimation of technical and environmental efficiency: An application to Dutch dairy farms. *American Journal of Agricultural Economics*, 81(1), 44–60.
- Rondinelli, D. A., & Berry, M. A. (2000). Environmental citizenship in multinational corporations: social responsibility and sustainable development. *European Management Journal*, 18(1), 70–84.
- Ross, A., & Droge, C. (2002). An integrated benchmarking approach to distribution center performance using DEA modeling. *Journal of Operations Management*, 20(1), 19–32.
- Sahoo, B. K., Luptacik, M., & Mahlberg, B. (2011). Alternative measures of environmental technology structure in DEA: An application. *European Journal of Operational Research*, 215(3), 750–762.
- Santos, G., Murmura, F., & Bravi, L. (2018). SA 8000 as a tool for a sustainable development strategy. *Corporate Social Responsibility and Environmental Management*, 25(1), 95–105.
- Schaltegger, S., & Sturm, A. (1990). Ökologische Rationalität-Ansatzpunkte zur Ausgestaltung von Ökologieorientierten Managementinstrumenten. *Die Unternehmung*, 4(4), 273–290.
- Scheel, H. (2001). Undesirable outputs in efficiency valuations. *European Journal of Operational Research*, 132(2), 400–410.
- Seiford, L. M., & Zhu, J. (2002). Modeling undesirable factors in efficiency evaluation. *European Journal of Operational Research*, 142(1), 16–20.
- Shen, C., Huang, C. Y., & Chu, P. Y. (2003). A performance evaluation model for governmental conflict management organisations: A study of labour management departments. *International Journal of Management and Decision Making*, 4(4), 312–336.
- Strezov, V., Evans, A., & Evans, T. J. (2017). Assessment of the economic, social and environmental dimensions of the indicators for sustainable development. *Sustainable Development*, 25(3), 242–253.
- Sueyoshi, T., Goto, M., & Sugiyama, M. (2013). DEA window analysis for environmental assessment in a dynamic time shift: Performance assessment of US coal-fired power plants. *Energy Economics*, 40, 845–857.
- Sueyoshi, T., & Sekitani, K. (2007). The measurement of returns to scale under a simultaneous occurrence of multiple solutions in a reference set and a supporting hyperplane. *European Journal of Operational Research*, 181(2), 549–570.
- Sun, L., & Stuebs, M. (2013). Corporate social responsibility and firm productivity: Evidence from the chemical industry in the United States. *Journal of Business Ethics*, 118(2), 251–263.
- Tajbakhsh, A., & Hassini, E. (2018). Evaluating sustainability performance in fossil-fuel power plants using a two-stage data envelopment analysis. *Energy Economics*, 74, 154–178.
- Tatari, O., Egilmez, G., & Kurmapu, D. (2016). Socio-eco-efficiency analysis of highways: A data envelopment analysis. *Journal of Civil Engineering and Management*, 22(6), 747–757.
- Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, 130(3), 498–509.
- Tuczek, F., Castka, P., & Wakolbinger, T. (2018). A review of management theories in the context of quality, environmental and social responsibility voluntary standards. *Journal of Cleaner Production*, 176, 399–416.
- Tyteca, D. (1996). On the measurement of the environmental performance of firms—A literature review and a productive efficiency perspective. *Journal of Environmental Management*, 46(3), 281–308.
- UN (United Nations) (2015). *Transforming our world: The 2030 agenda for sustainable development*. Resolution adopted by the General Assembly on 25 September 2015.
- Vajnhandl, S., & Valh, J. V. (2014). The status of water reuse in European textile sector. *Journal of Environmental Management*, 141(1), 29–35.
- Wang, L., Chen, Z., Ma, D., & Zhao, P. (2013a). Measuring carbon emissions performance in 123 countries: Application of minimum distance to the strong efficiency frontier analysis. *Sustainability*, 5(12), 5319–5332.
- Wang, Q., Hang, Y., Sun, L., & Zhao, Z. (2016). Two-stage innovation efficiency of new energy enterprises in china: A non-radial DEA approach. *Technological Forecasting and Social Change*, 112, 254–261.

- Wang, Y., Sun, M., Wang, R., & Lou, F. (2015). Promoting regional sustainability by eco-province construction in china: A critical assessment. *Ecological Indicators*, *51*, 127–138.
- Wang, K., Xian, Y., Lee, C., Wei, Y., & Huang, Z. (2017). On selecting directions for directional distance functions in a non-parametric framework: A review. *Annals of Operations Research*. <https://doi.org/10.1007/s10479-017-2423-5>
- Wang, K., Yu, S., & Zhang, W. (2013b). China's regional energy and environmental efficiency: A DEA window analysis based dynamic evaluation. *Mathematical and Computer Modelling*, *58*(5–6), 1117–1127.
- WBCSD (World Business Council For Sustainable Development) (2005). *Eco-efficiency learning module*. <http://www.wbcsd.org/pages/EDocument/EDocumentDetails.aspx?ID=13593>. Accessed 30 July 2017.
- WCED (World Commission on Environment and Development). (1987). *Our common future*. Oxford: Oxford University Press.
- Wu, J., An, Q., Yao, X., & Wang, B. (2014a). Environmental efficiency evaluation of industry in China based on a new fixed sum undesirable output data envelopment analysis. *Journal of Cleaner Production*, *74*(1), 96–104.
- Wu, P., Huang, T., & Pan, S. (2014b). Country performance evaluation: The DEA model approach. *Social Indicators Research*, *118*(2), 835–849.
- Wursthorn, S., Poganietz, W., & Schebek, L. (2011). Economic–environmental monitoring indicators for european countries: A disaggregated sector-based approach for monitoring eco-efficiency. *Ecological Economics*, *70*(3), 487–496.
- Xiong, B., Li, Y., Santibanez Gonzalez, E. D. R., & Song, M. (2017). Eco-efficiency measurement and improvement of Chinese industry using a new closest target method. *International Journal of Climate Change Strategies and Management*, *9*(5), 666–681.
- Yang, W. C., Lee, Y. M., & Hu, J. L. (2016). Urban sustainability assessment of Taiwan based on data envelopment analysis. *Renewable and Sustainable Energy Reviews*, *61*, 341–353.
- Yang, H., & Pollitt, M. (2009). Incorporating both undesirable outputs and uncontrollable variables into DEA: The performance of Chinese coal-fired power plants. *European Journal of Operational Research*, *197*(3), 1095–1105.
- Yin, K., Wang, R., An, Q., Yao, L., & Liang, J. (2014). Using eco-efficiency as an indicator for sustainable urban development: A case study of Chinese provincial capital cities. *Ecological Indicators*, *36*, 665–671.
- Yu, S. H., Gao, Y., & Shiue, Y. C. (2017). A comprehensive evaluation of sustainable development ability and pathway for major cities in China. *Sustainability*, *9*(8), 1483.
- Zanella, A., Camanho, A. S., & Dias, T. G. (2015). Undesirable outputs and weighting schemes in composite indicators based on data envelopment analysis. *European Journal of Operational Research*, *245*(2), 517–530.
- Zhou, P., Ang, B. W., & Zhou, D. Q. (2010). Weighting and aggregation in composite indicator construction: A multiplicative optimization approach. *Social Indicators Research*, *96*(1), 169–181.
- Zhou, P., Poh, K. L., & Ang, B. W. (2007). A non-radial DEA approach to measuring environmental performance. *European Journal of Operational Research*, *178*(1), 1–9.
- Zhou, H., Yang, Y., Chen, Y., & Zhu, J. (2018). Data envelopment analysis application in sustainability: The origins, development and future directions. *European Journal of Operational Research*, *264*(1), 1–16.
- Zhu, J. (1996). Data envelopment analysis with preference structure. *The Journal of the Operational Research Society*, *47*(1), 136–150.