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Application of Data Envelopment Analysis for Assessment of Eco-Efficiency of Food Shops at Phuket Island, Thailand

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Abstract

Located in the southeast of Thailand, Phuket is an eminent tourist destination not only for its natural splendor but also for its culinary development. In 2015, the island was recognized as a "City of gastronomy" by the United Nations Educational, Scientific and Cultural Organization (UNESCO) proving the undeniable influence of food services on the prosperity of the tourism industry at this island. Together with the aim to increase revenue from the gastronomy, Phuket has also committed to developing responsible and sustainable production and consumption of local food resources. As a contribution to a more balanced development of food services, this study aims to investigate the performance efficiency of food service at Phuket Island in terms of environmental and economic aspects. Data Envelopment Analysis (DEA) had been adopted to study the comparative efficiency performances of 298 food shops at Phuket Island, based on the input and output of the food shops during the operational process. The results being interpreted for different aspects with different comparisons showed the relationship between input (i.e. utility consumption), undesirable output variables (i.e., greenhouse gas (GHG) emissions, and waste disposal), and desirable output (i.e., net profit) in the studied food shops. It was revealed that the electricity consumption accounted for the major share in terms of utility consumption and GHG emission, resulting in the most notable impact on the efficiency score, which was evaluated based on the input and output of the food shops during the operational process. Food shops with lower electricity consumption are clarified as the majority of food shops having a high efficiency score. The surrounding area also played an important role in the efficiency score of the food shops. Food shops in the areas with well-known tourist destinations, such as central Thalang District, southeastern Mueang District, and southwestern Kathu District were more efficient than the food shop in more remote locations such as eastern Thalang District and the northeastern part of Kathu District which are rural areas covered by a variety of mountains and forests with low population.

Keywords : Data Envelopment Analysis; Eco-efficiency; Food service; Phuket Island; Tourism; Food shop

Introduction

As a tourist hub of the region, Phuket - a popular island in Thailand - is one of the fastest developing provinces in Thailand in terms of economy and society, mainly due to the development of tourism [1]. It is the second most visited destination in Thailand after Bangkok, accounting for nearly one-third of all visitors to Thailand. According to statistics from the Tourism Authority of Thailand (TAT), Phuket received about 8.4 million international tourists in 2013, contributing over USD 6.99 billion to the province's revenue [2]. In 2016, the number of international tourists coming to Phuket increased considerably to over 9.6 million people, resulting in an economic contribution of over 10 billion USD [3]. Tourism was expected to be a promising industry in Phuket in the coming years.

Within the tourism industry, expenditure on food has long been one of the largest shares, accounting for about one third of tourists' spending [4]. In the case of Phuket, the food shop business also has a major impact on the economy. On average, a tourist in Phuket spends approximately 43 USD per day on food and drink, accounting for almost a fifth of a tourist's total expenditure per day. This proportion is even higher for travelers (who do not spend on accommodation); they spend about 30% of their budget on food and drinks. Furthermore, Phuket is also a particular representative of Thai cuisine. In 2015, the local government of Phuket joined the Creative Cities Network of the United Nations Educational, Scientific and Cultural Organization (UNESCO), and Phuket was the first city in ASEAN to be awarded the title of Creative City of Gastronomy [5]. This could be beneficial for Phuket to attract more tourists and develop the city's tourism business. The development of tourism, especially gastronomy, could be an advantage, but it also has some harmful effects on the island's environment. The demand for natural resources in Phuket has increased in response to the increase in tourist arrivals, the number of people eating out, and the number of food shops. Therefore, food shops also have an important link to environmental responsibility as they can be considered one of the largest consumers of resources (e.g., energy and water) and disposers of waste, especially food waste. Due to the significant impact of the hospitality industry on the environment, sustainable tourism research should be extended to food-related areas. Examining the inputs, outputs, and practical benefits of the enterprise gives us a more comprehensive view of sustainability.

The main idea of the eco-efficiency (EE) concept is to create more value with fewer impacts on the environment and less consumption of natural resources, thus bringing together environmental improvements that yield parallel economic benefits [6]. The effectiveness of the approaches is assessing the environmental performance of industrial systems and products using single performance factors, such as energy efficiency or fuel efficiency. However, multiple performance factors are often needed for a comprehensive holistic measurement as efficiency evaluation has become more complex and multidisciplinary [7]. Thanawong et al. [8] studied the EE of rice crops in Thailand. While their study offers a reasonable proxy for sustainability analysis, it has an issue of multiple EE ratios (the same number of environmental impacts included). To solve this problem, a weighted totality of the numerous environmental impacts is usually employed to construct an incorporating environmental impact score. The crucial question is how the weights should be selected or determined. DEA combined with EE was considered to be a solution for aggregating different environmental pressures to construct an encompassing of EE indicators.

DEA is a well-known mathematical procedure that uses a nonparametric linear programming technique to evaluate the relative efficiency of a set of similar entities named decision making units (DMUs) such as public organizations and the private sector, or even regions and countries [9]. This method is employed to determine the weights of each environmental impact when building an incorporating environmental impact score. In the traditional DEA (T-DEA), a DMU can attain its maximum efficiency score using its most promising multiplier weights. It has been applied to recognize the efficient DMUs performing best practices and to assist the improvement of the inefficient units by providing optional targets to increase outputs or lessen inputs [10]. In the case of having more than one DMU assessed as efficient, Shannon's entropy DEA (S-DEA), a method developed to calculate optimal weights with the importance degree, can help offer further discrimination among them [11]. Therefore, using both T-DEA and S-DEA models can help to enhance the benefit of using DEA approach.

Despite an increase in DEA applications for efficiency measurement, there is a shortage of research employing this method in the food shops. Most of the research using DEA are in the context of airline industry, other few research focus on restaurants in the USA, European and other countries in Asia [12] such as Iran [13] and Taiwan [14]. However, the results from international studies using DEA for evaluating restaurant efficiency might not be applicable to the Phuket food shops due to a different geographical and economic context [15]. Because of the significance of food shops in tourism industry, studies in this setting were conceptualized. The hypothetical influence relates to driving factors affecting food shop efficiency from a study, where such findings could reflect similarities and differences that could be supportive for operational and management endeavors [12]. Hence, the aim of this study is to evaluate the performance efficiency of food shops in Phuket in terms of environmental and economic aspects using T-DEA and S-TEA.

Materials and Methods

1. Study area

Phuket is located at 7°53'24" N and 98°23'54" E in the south of Thailand. It is the largest island province in Thailand, consisting of 39 smaller islands. It lies off the west coast of Thailand in the Andaman Sea and stretches 49 km from north to south and 19 km from east to west with a total area of 570 km^2 including the province's other islands. Phuket is divided into three districts, which are further subdivided into 17 sub-districts, and 103 villages.

2. Methods

This study uses primary data obtained from questionnaire surveys from different food shops in Phuket for the efficiency assessment. The data collection was conducted in 2017 to early 2018. T-DEA and S-DEA methods are employed to determine the efficiency performances of food service. The research process is presented in Figure 1.

2.1 Questionnaire

A total of 925 questionnaires were filled out. However, the dataset was screened and trimmed to produce the minimum relative error. Finally, data from 298 sampled food shops were analyzed. The distribution of surveyed objects is shown in Figure 2. The distribution of the samples is not widely ranged around Phuket based on food shops' locations. Also, it depends on the food shops' consent to complete the survey.

The survey used both open-ended and close-ended questions both in English and Thai. Participants in the study group were chosen by stratified random sampling into three districts of Phuket Province. The questionnaire provided the information on types of the food shop (i.e., Air conditioning (AC), non air conditioning (Non-AC), and hawker), type of cuisine (Thai/Phuket food, international food, dessert/beverage, and others), costs of operation (electricity fee, tap water fee, and cooking gas), and average profit.

2.2 Eco-efficiency calculation

Considering environmental influence, the WBCSD [16] states the following types of consumption as applicable indicators: energy, materials, water, and GHG emissions. In this research, resource consumption (including electricity, LPG, fuel, and water) and GHG emissions from the utility consumption were focused on.

For the economic value part, Seppälä et al. [17] suggested three economic indicators to represent the value of products and services in regional EE analysis, that is, GDP, value added of industries and output at basic prices. In consideration that our research focuses on the efficiency of small-to-medium enterprises, the net profit margin of food shops was selected to represent value of products and services.

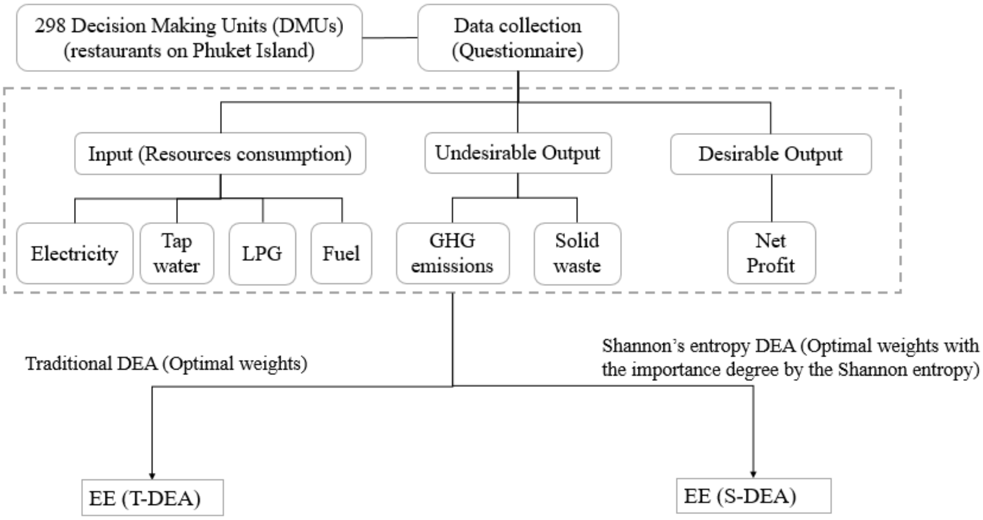

Figure 1 Flowchart of research process

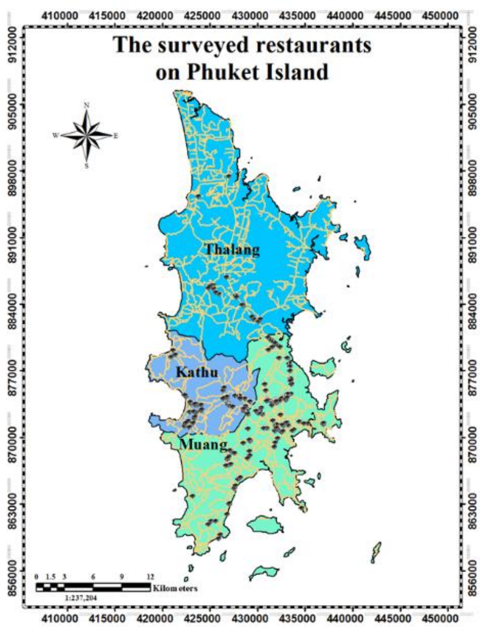

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Figure 2 Location of 298 surveyed food shops on Phuket Island

Treating the undesirable outputs like classic inputs to be minimized in DEA model was already valued as an intuitive approach [18]. In this study, the undesirable outputs were envisioned as inputs in the DEA model for EE analysis.

The EE, which is the efficiency score (θ), is calculated as the ratio of weighted sum of outputs to its weighted sum of inputs as [9]:

$$\theta = \frac{weighted\ sum\ of\ outputs}{weighted\ sum\ of\ inputs} \quad (1)$$

A DMU is considered as efficient if its efficiency score is 1. DEA method is applied to determine weights of input and output of each DMU. It is supposed that in a DEA problem, there are n DMUs with m inputs and s outputs. The vectors $x_j = [x_{1j}, x_{2j}, \dots, + x_{mj}]$ and $y_j = [y_{1j}, y_{2j}, \dots, + y_{sj}]$ are used to denote the inputs and outputs of DMU_j respectively, in which $j = 1, 2, \ldots, n$. Then the efficiency of certain DMU_{j0} ($j_0 = 1, 2, \ldots, n$) is defined as follows [9]:

$$\theta = \frac{u_1 y_{1j_0} + u_2 y_{2j_0} + \ldots + u_s y_{sj_0}}{v_1 x_{1j_0} + v_2 x_{2j_0} + \ldots + v_m x_{mj_0}} = \frac{\sum_{r=1}^{s} u_{rj_0} y_{rj_0}}{\sum_{t=1}^{m} v_{tj_0} x_{tj_0}}$$

$$\text{Maximize } \theta = \frac{\sum_{r=1}^{s} u_{rj_0} y_{rj_0}}{\sum_{t=1}^{m} v_{tj_0} x_{tj_0}} \qquad (2)$$

$$\text{s.t.} \quad \frac{\sum_{r=1}^{s} u_{rj_0} y_{rj_0}}{\sum_{t=1}^{m} v_{tj_0} x_{tj_0}} \leq 1 \qquad j = 1,2, \ldots, n$$

$$u_r, v_t \geq 0$$

in which $v_{j_0} = [v_{1j_0}, v_{2j_0}, \ldots, + v_{mj_0}]$ and $u_{j_0} = [u_{1j_0}, u_{2j_0}, \ldots, + u_{sj_0}]$ are the multiplier weights of inputs and outputs, respectively; θ is the efficiency of the DMU_{j0} under consideration; s is the number of outputs ($r = 1,2, \ldots, s$); m is the number of inputs ($t = 1,2, \ldots, m$) and j denotes jth DMUs ($j = 1,2, \ldots, n$).

In this study, the units of assessment chosen are food shops. There are two efficiency scores for each DMU. The EE (T-DEA) is an efficiency score calculated based on a set of optimal weights computed by traditional DEA, while EE (S-DEA) is an efficiency score calculated based on a set of weights with the importance degree computed by Shannon's entropy DEA.

2.2.1 Traditional DEA

Envisioning the undesirable outputs as inputs, this idea leads to the following approach, which is called equation 3:

$$\text{Maximize } \frac{\sum_{r=1}^{k} u_{rj_0} y_{rj0}}{\sum_{t}^{m} v_{tj_0} x_{tj_0} + \sum_{r=k+1}^{s} u_{rj_0} y_{rj0}}$$

s.t.

$$\frac{\sum_{r=1}^{k} u_{rj_0} y_{rj}}{\sum_{t}^{m} v_{tj_0} x_{tj} + \sum_{r=k+1}^{s} u_{rj_0} y_{rj}} \leq 1 \qquad (3)$$

$$j = 1,2, \ldots, n; \; u, v \geq 0$$

$$t = 1,2, \ldots, m; \; r = 1,2, \ldots, s$$

The model assigns an efficiency score between 0 and 1 for each DMU after evaluation, with "1" being the efficiency frontier.

2.2.2 Shannon's entropy DEA

In this study, the estimation of food shops' efficiency performances follows the proposed methodology that comes from Qi and Guo [11]. In order to improve the discriminating power of the DEA method, they proposed a methodology using Shannon's entropy to aggregate different sets of optimal weights into a 'common set of weights' (CSW). Then DMUs could be evaluated with this CSW. The proposed methodology can be formulated as the six steps presented below.

Step 1: Data normalization.

In this study, there is no outlier data in inputs and outputs after the data screening process. For convenience of comparison, the input $x_{tj_0} (t = 1,2, \ldots, m)$ and output $y_{rj_0} (r = 1,2, \ldots, s)$ of $DMU_{j_0} (j_0 = 1,2, \ldots, n)$ are normalized as follows:

$$\begin{cases} x_{tj_0} = x_{tj_0} / \, max_{j \in \{1,2,\ldots,n\}} \{x_{tj}\} \\ y_{rj_0} = y_{rj_0} / \, max_{j \in \{1,2,\ldots,n\}} \{y_{rj}\} \end{cases} \qquad (4)$$

Normalizing residuals by transforming all input and output variables in the data to a common scale of [0;1].

Step 2: Non-zero optimal weights calculation.

In this step, a modified weight restriction model was proposed for calculating non-zero optimal weighs as follows. At the end of this step, a set of non-zero optimal weights for every DMU can be attained. The optimal weights of inputs and outputs are denoted by V and U respectively, as follows:

$$V = \begin{bmatrix} v_{11} & v_{21} & \cdots & v_{m1} \\ v_{12} & v_{22} & \cdots & v_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ v_{1n} & v_{2n} & \cdots & v_{mn} \end{bmatrix} \begin{matrix} \leftarrow & DMU_1 \\ \leftarrow & DMU_2 \\ \leftarrow & \vdots \\ \leftarrow & DMU_n \end{matrix} \qquad (5)$$

$$U = \begin{bmatrix} u_{11} & u_{21} & \cdots & u_{s1} \\ u_{12} & u_{22} & \cdots & u_{s2} \\ \vdots & \vdots & \ddots & \vdots \\ u_{1n} & u_{2n} & \cdots & u_{sn} \end{bmatrix} \begin{matrix} \leftarrow & DMU_1 \\ \leftarrow & DMU_2 \\ \leftarrow & \vdots \\ \leftarrow & DMU_n \end{matrix} \qquad (6)$$

Step 3: Weights normalization.

The normalization of the non-zero optimal weighs is prepared for the calculation of Shannon's entropy. The optimal weights

$v_{t_0 j_0}(t_0 = 1,2,\dots,m)$ and $u_{r_0 j_0}(r_0 = 1,2,\dots,s)$ of $DMU_{j_0}(j_0 = 1,2,\dots,n)$ are normalized as follows:

$$\begin{cases} \alpha_{t_0 j_0} = v_{t_0 j_0} / \sum_{t=1}^{m} v_{t j_0} \\ \beta_{r_0 j_0} = u_{r_0 j_0} / \sum_{r=1}^{s} u_{r j_0} \end{cases} \quad (7)$$

In this step, the non-zero input weights and output weights are normalized separately.

Step 4: Shannon's entropy calculation.

The Shannon entropy of $DMU_{j_0}(j_0 = 1,2,\dots,n)$ for inputs and outputs are calculated as follows:

$$\begin{cases} e_{j_0}^{input} = -e_0 \sum_{t=1}^{m} \alpha_{t j_0} \ln(\alpha_{t j_0}) \\ e_{j_0}^{output} = -e_1 \sum_{r=1}^{s} \beta_{r j_0} \ln(\beta_{r j_0}) \end{cases} \quad (8)$$

in which e_0 and e_1 are the entropy constants and defined as $e_0 = (ln\, m)^{-1}$ and $e_1 = (ln\, s)^{-1}$. $\alpha_{t j_0}$ and $\beta_{r j_0}$ are probabilities of occurance of outcome.

It is supposes that there are always more than one inputs or more than one outputs which implies that $m > 1$ or $s > 1$. Especially, the entropy of single input or single output is defined as 0.

Step 5: The importance degree of optimal weights determination.

The importance degree of $DMU_{j_0}(j_0 = 1,2,\dots,n)$ is defined as follows:

$$w_{j_0} = (e_{j_0}^{input} + e_{j_0}^{output}) / (\sum_{j=1}^{n} e_j^{input} + \sum_{j=1}^{n} e_j^{output}) \quad (9)$$

The degree of importance is accordance with maximizing the Shannon entropy. In fact, the importance degree determined by the Shannon entropy is based on the difference of both inputs weights and outputs weights. It means that both inputs weights and outputs weights are combined to identify the importance degree of every DMU.

Step 6: The common weights determination.

The common weights $v = [v_1, v_2, \dots, v_m]^T$ and $u = [u_1, u_2, \dots, u_s]^T$ are the aggregation of the optimal weights from every DMU with the importance degree by the Shannon entropy. After this step, all DMUs have only one set of common weights for each input/output variable. It should be noted that the optimal weights used here are the optimal weights before the weights normalization as follows:

$$\begin{cases} v_t = \sum_{j=1}^{n} (w_j v_{tj}) \\ u_r = \sum_{j=1}^{n} (w_j u_{rj}) \end{cases} \quad (10)$$

in which *t = 1,2, …, m and r = 1,2 ,…, s*

After these six steps, DMUs can be evaluated with the common weights v and u. The DEA models with Shannon's entropy were run using Premium Solver Platform 2019 software.

Results and Discussion

This section shows the assessment results of 298 food shops' performance and some factors that significantly affects their efficiency scores such as type of food shops (AC, Non-AC or hawker) or the food shops' locations.

1. Relationship between EE and resources consumption

This part shows the result of performance efficiency assessment based on the utility consumptions (electricity, tap water, LPG, fuel), GHG emissions, and solid waste as inputs, and the net profit margin of food shops as an output. It is evident that in every subgroup, surveyed DMUs spent most of their money on LPG and electricity (Figure 3).

It can be seen that the food shop AC type had a significant electricity consumption of 2,289 USD per year, accounting for 61% of the total expenditure and seven times higher than that of the hawker type, which consumed the least electricity. This is due to the cooling and ventilation systems, especially the use of AC which is a high energy-consuming machine. According to Energy Star [19], ventilation, and AC systems account for 28% of the total energy consumption in food shops. Another study also found that ventilation and AC systems, together with water and cooking accounted for more than 90% of total energy demand [20]. As a result, this type of food shop was the most inefficient compared to the Non-AC type and hawker type with an average efficiency score of only 0.505. In contrast, since hawker is a mobile business, the use of electricity in this type of food shop is not essential. Therefore, hawker had the highest efficiency score of 0.896 for T-DEA and 0.595 for S-DEA. Its small operational size, low resource consumption, and low maintenance requirement are the reasons for the relatively high efficiency score.

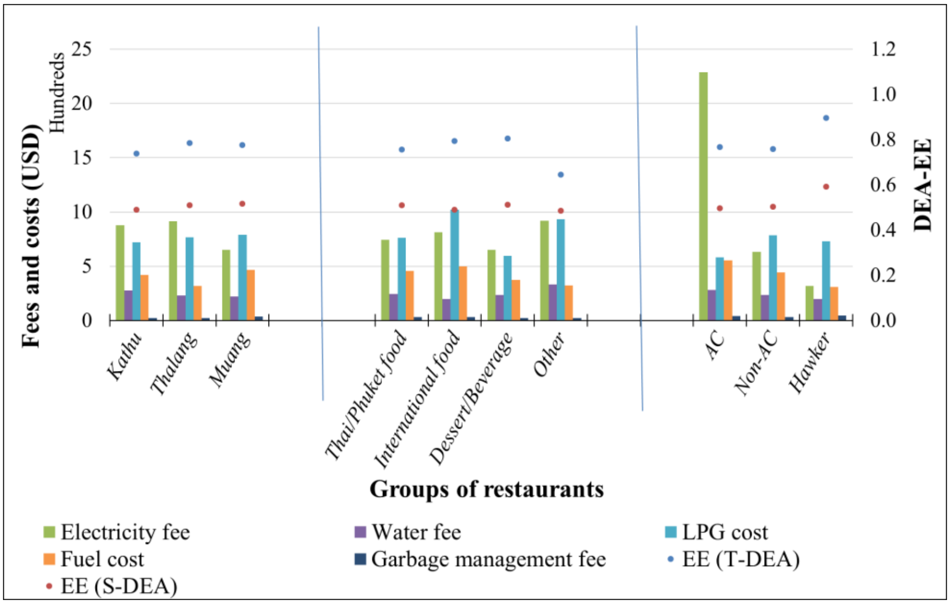

Figure 3 Utility and waste fees/costs and EE performances in different groups of food shop

2. EE performances of different food shop groups

Figure 4 indicates that the studied food shops generated a total of 1,643,973 kg of CO_2-equivalents (CO_2-eq), of which the largest share of 991,388 kg of CO_2-eq (slightly more than 60% of the total) was electricity consumption required for the use of equipment such as lighting, cooking, cooling, refrigeration, and ventilation. Interestingly, solid waste generation was the second largest source of the total GHG emissions from food shops at 416,244 kg CO_2-eq (more than 25% of the total), as food waste is one of the largest contributors to increased GHG generation [21]. The amount of CO_2-eq emissions from tap water use was slightly lower at 72,151 kg CO_2-eq (about 5% of the total). The reason for the high GHG emissions from electricity use but the low number from tap water use was because many food shops used electricity to pump groundwater instead of purchasing fresh water from Provincial Waterworks Authority.

For LPG and fuels, GHG emissions came from LPG consumption, which accounted for 116,167 kg CO_2-eq due to cooking needs. Fuel for transportation is not used to any extent by the food shops; therefore, GHG emissions from fuel consumption were minimal (about 48,023 kg CO_2-eq or about 3% of the total).

Among the three districts of Phuket (e.g., Kathu, Thalang, Mueang), the result shows that the mean efficiency score of Kathu district is the lowest compared to all other districts, with 0.739 under T-DEA and 0.490 under S-DEA. This could be due to the GHG emissions of the DMUs of this district as their average value was the highest at 1,250 kg CO_2-eq. compared to the other districts. However, there was a change in rank between Thalang district and Mueang district in the two models. Under T-DEA, Thalang was relatively the most efficient district with a mean of 0.786, but fell to second place under S-DEA (EE = 0.509). In contrast, although Mueang was rated as more inefficient than Thalang at T-DEA (EE = 0.777), S-DEA of Mueang (EE= 0.516) was higher than that of Thalang.

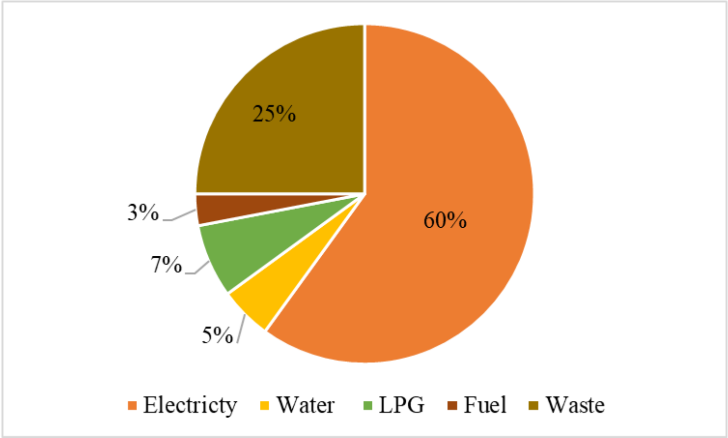

Figure 4 Contributions of each factors to total GHG emissions

The highest efficiency scores belong to the center of Thalang, the southeast of Mueang, and the southwest of Kathu. It should be noted that the mentioned zones are the most famous and busy places in the districts, such as central Thalang with Phuket International Airport, southeastern Mueang with Phuket City – the capital of Phuket Province, and southwestern Kathu with Patong Town Municipality – the center of Phuket's nightlife and shopping, which is located in the coastal area of Kathu district. On the other hand, the east of Thalang and the northeast part of Kathu had lowest efficiency score. These areas are considered as rural areas where mainly local people are engaged in livestock or cultivation of rice, fruits and perennial plants, vegetables and ornamental plants. In addition, these areas are surrounded by mountains and forests. Therefore, there are limited tourists and food services in these areas.

Out of the 298 DMUs, 42 were evaluated as the most efficient by both methods, namely T-DEA and S-DEA. Figure 5 shows that 62% of these 42 most efficient DMUs were located in Mueang district, especially around Phuket City - the capital of Phuket Province, which is an attraction in itself. The district has retained its provincial charm and has a historic old town with many food shops, cafes and night markets that attract thousands of visitors. In addition, Kathu district has a significant number of efficient DMUs, accounting for just over 26% of the total. Most of the efficient food shops in this district came from the populated area (Patong Town Municipality). As mentioned earlier, Patong is one of the most attractive tourist destinations in Phuket and therefore is mainly visited by tourists. Thus, the food shops in this area received a significant contribution from this typical group of customers, which in a way has a positive impact on their profit and efficiency. This result is in accordance with the findings by Mhlanga [11], who found that food shop locations have a statistically substantial relationship with their efficiency. This author also proved that food shops positioned in, or nearby, well-known destinations had higher efficiency scores than those in distant locations [11], due to the convenience of traveling. Hence, several food shops' facilities such as air conditioners or lighting systems served more customers at the same time. It helps increase food shops' income.

In the end, both T-DEA and S-DEA could reveal different issues. For S-DEA, electricity consumption had the highest value of weight, indicating that this parameter was the most demanded by all DMUs. In fact, an enormous amount of electricity is consumed in Phuket, especially for tourism activities. Electricity consumption is also the factor that has the largest contribution to the total GHG emissions in this study. For T-DEA, water had the least slacks, implying that the least reduction of water consumption (compared to other resources) can help most DMUs to reach their maximum efficiency.

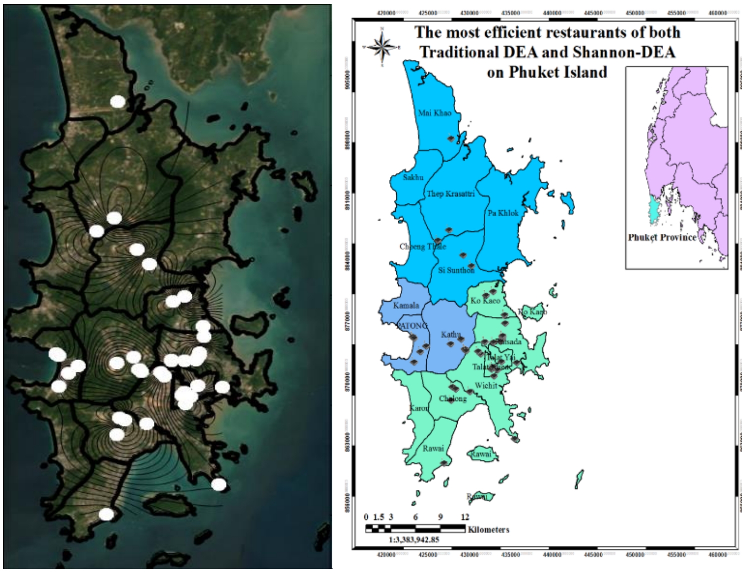

Figure 5 Distribution of the most efficient DMUs

Conclusions

The performance assessment of 298 food shops in Phuket Island was conducted using EE combined with DEA. Many conclusions can be drawn from this study as follows.

The studied food shops studied generated a total of 1,643,973 kg CO_2-eq, of which electricity consumption accounted for the largest share at 991,388 kg CO_2-eq (just over 60% of the total). Solid waste was the second largest source of total GHG emissions from food shops at 416,244 kg CO_2-eq (more than 25% of the total). Tap water, LPG, and fuel consumption accounted for 236,341 kg CO_2-eq (about 15% of the total).

Among the three food shop types considered, hawker had the highest efficiency score. However, the performance of food shops with and without AC depended on the indicator used for the assessment. Electricity consumption might have the greatest impact on the efficiency of the food shops as suggested by the common set of weights' values of S-DEA. Food shops with air conditioners had significant electricity consumption due to the cooling and ventilation systems.

The analysis using T-DEA showed Mueang district was the most efficient area, followed by Thalang and Kathu. The result was slightly different when using S-DEA, where Thalang district was the most efficient area, followed by Mueang and Kathu. The most efficient zones in Phuket Islands were the center of Thalang, the southeast of Mueang, and the southwest of Kathu because they are the most famous and visited places on the island. In contrast, the east of Thalang and the northeast part of Kathu were the most inefficient zones as they are considered more rural areas covered by a wide range of mountains and forests with limited population. Therefore, food shops in or near cities with more prevalent destinations were more efficient than food shops in distant areas.

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