Production efficiency of animal feed obtained from food waste in Japan

Tomoaki Nakaishi1 · Hirotaka Takayabu2

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Abstract
Converting food waste into animal feed is highly useful for tackling the problem of food waste, which is particularly severe in developed countries. This study quantified the inefficiencies in converting food waste into animal feed and identified the sources of inefficiencies through a data envelopment analysis (DEA) of the monthly input–output data of two food waste–based animal feed producers in Japan. Our empirical analysis revealed that the producers of animal feed obtained from food waste (especially those treating food waste from retail and service industries) demonstrated inefficiencies in production technology and scale; moreover, expanding the production scale and improving the quality of food waste could enhance production efficiency. Based on the empirical results, specific policy implications were provided for the widespread use of animal feed obtained from food waste in Japan and elsewhere, globally. Furthermore, it was suggested that the COVID-19 pandemic contributed to a severe reduction in the production efficiency of animal feed producers treating food waste obtained from retail and service industries.

Keywords Production efficiency · Data envelopment analysis · Food waste · Animal feed · COVID-19

Abbreviations

| Abbreviation | Description |
|--------------|-------------|
| CAA          | Consumer Affairs Agency |
| COVID-19     | Coronavirus disease 2019 |
| CV           | Coefficient of variation |
| CRS          | Constant returns to scale |
| DEA          | Data envelopment analysis |
| DMU          | Decision-making unit |
| EU           | European Union |
| FAO          | Food and Agriculture Organization of the United Nations |
| GHG          | Greenhouse gas |
| IRS          | Increasing returns to scale |
| LCA          | Life cycle assessment |
| LCC          | Life cycle cost |
| MAFF         | Ministry of Agriculture, Forestry, and Fisheries of Japan |
| ME           | Ministry of the Environment of Japan |
| FPP          | Fractional programming problem |
| NIRS         | Non-increasing returns to scale |
| PTE          | Pure technical efficiency |
| QFW          | Quality of food waste |
| RTS          | Returns to scale |
| SBM          | Slacks-based measure |
| SDG          | Sustainable development goal |
| SE           | Scale efficiency |
| SP           | Slack proportion |
| TDN          | Total digestible nutrient |
| TE           | Technical efficiency |
| UK           | United Kingdom |
| UNEP         | United nations environment program |
| US           | United States |
| VRS          | Variable returns to scale |
| WFP          | World Food Program |

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Tomoaki Nakaishi
tomoaki.nakaishi@gmail.com

1 International Institute for Carbon Neutral Energy Research (I2CNER), Kyushu University, 744 Motoooka, Nishi-ku, Fukuoka 819-0395, Japan
2 Department of Management and Business, Kindai University, Fukuoka, Japan
Introduction

According to the Food and Agriculture Organization of the United Nations (FAO) (2018), ~800 million people worldwide suffered from hunger and malnutrition in 2017, and ~150 million children under the age of five suffered from stunting. Conversely, global food waste is estimated to be ~1.3 billion tons per year, which is roughly one-third of global production (FAO 2011). Food is progressively disposed of in the process from production to consumption (i.e., the food supply chain). In developing countries, food waste at the consumption stage is considerably low, whereas most food waste in developed countries occurs at this stage (Ministry of Agriculture, Forestry, and Fisheries of Japan (MAFF); Ministry of the Environment of Japan (ME) 2013). In addition, this imbalance in food waste between developed and developing countries is also known to cause global energy and environmental waste. In expanding global supply chains, additional amounts of food with high water content are produced in places where it is not directly consumed and is transported and disposed of over long distances, resulting in wasteful use of fossil fuels and increased greenhouse gas (GHG) emissions (MAFF 2020a). To address these issues, the sustainable development goals (SDGs) established at the 2015 United Nations Summit called for “zero hunger (target 2),” “good health and well-being (target 3),” “affordable and clean energy (target 7),” “responsible consumption and production (target 12),” and “climate action (target 13)” (United Nations Environment Programme (UNEP) 2015). In particular, the calls to “halve per capita global food waste by 2030 at retail and consumer levels and reduce food losses along production and supply chains, including post-harvest losses (target 12.3)” and to “substantially reduce waste generation by 2030 through prevention, reduction, recycling, and reuse (target 12.5)” were directly related to food waste.

Food waste is severe in Japan, which is a developed country. In 2016, food waste in Japan amounted to ~27.59 million tons (business waste: 19.70 million tons; household waste: 7.89 million tons), being one of the worst, globally (MAFF 2020a). In particular, 6.43 million tons (23%) of food waste (hereafter, edible food waste) was discarded despite being edible, which is 1.6 times the amount of food aid provided by the World Food Program (WFP) (~3.9 million tons) (Consumer Affairs Agency (CAA) 2020; WFP 2017). Furthermore, the disposal of food waste incurs huge social costs (~2 trillion yen per year), and the shortage of landfill sites is also a challenge (CAA 2020; Liu et al. 2016). The Japanese government aims to halve edible food waste in both business and household waste by 2030 (CAA 2020).

The reduction of business food waste (including food manufacturing, wholesaling, retailing, and service industries in Japan is mainly promoted through the following four methods: conversion to animal feed, conversion to fertilizers, utilization as biogas through methane fermentation (e.g., biogas power generation), and utilization as oil and fat products (e.g., production of biodiesel, paints, and inks) (MAFF and ME 2013). In particular, the use of business food waste as animal feed is the most popular method of recycling food waste in Japan. In fact, ~74% (9.13 million tons) of the total business food waste recycled in 2017 (12.3 million tons) was used as animal feed (MAFF 2020b). Animal feed produced from food waste (e.g., food dregs and expired food items in the process of food production, cooking, and selling) is called “eco-feed” in Japan. The production of eco-feed can not only contribute to the reduction of food waste, but can also help overcome the low rate of food self-sufficiency in Japan (Liu et al. 2016; Sugiura et al. 2009). Japan is extremely dependent on food imports, with a calorie-based food self-sufficiency rate of 37% in 2018, which is one of the lowest among developed countries (CAA 2020). In 2019, the food self-sufficiency rate in Japan was ~25%, and the majority (~88%) of the concentrated feed, such as soybean and corn, used by livestock farmers were imported (MAFF 2020b). The Japanese government has set a feed self-sufficiency target of 34% for 2030 to prevent livestock farmers from over-reliance on imported feed (MAFF 2020b). Moreover, MAFF (2020b) reported that the use of animal feed obtained from food waste, which is cheaper than imported feed, could help reduce the feeding cost and improve the feeding productivity for livestock farmers. Therefore, the Japanese government prioritizes reducing business food waste by converting it into animal feed and supports its production and dissemination by providing subsidies to related businesses (MAFF 2020b). In 2019, the production of animal feed from food waste in Japan amounted to ~1.19 million total digestible nutrient (TDN) tons (~6% of total concentrate feed), which has increased annually (MAFF 2020b).

The use of business food waste as animal feed has many advantages as mentioned above; however, its widespread use has challenges such as lack of safety, uneven nutritional composition, and high production costs (Sugiura et al., 2009). In general, food waste is prone to decay during collection, transportation, and storage owing to its high-water content; moreover, the quality of the animal feed produced from food waste is susceptible to deterioration (Sugiura et al., 2009). In addition, business food waste (especially from food retailing and service) is not always available in constant quantities and the nutritional content is not always homogeneous (Sugiura et al., 2009). These aspects are particularly influential in the feed-conversion process of business food waste obtained from food retailing and service. In fact, approximately 80% and 57% of the business food waste obtained
from food manufacturing and wholesaling generated in 2017 were recycled into animal feed and fertilizer, respectively. Conversely, approximately 39% and 20% of business food waste obtained from food retailing and service, respectively, were recycled (MAFF 2020b). Additionally, the use of food waste as animal feed is not yet globally widespread due to the risk of diseases such as foot-and-mouth disease and African swine fever (Salemdeeb et al. 2017; zu Ermgassen et al. 2016). In the European Union (EU), the use of food waste as animal feed was banned after the spread of foot-and-mouth disease in 2002 (Salemdeeb et al. 2017; zu Ermgassen et al. 2016). In contrast, in East Asian countries such as Japan and Korea, the heat treatment of collected food waste is mandatory while converting food waste to prevent infecting livestock with diseases (Salemdeeb et al. 2017; Sugiura et al. 2009; zu Ermgassen et al. 2016).

Quantifying the inefficiencies during the processing of food waste into animal feed and identifying their source is critical for enhancing the efficiency of the production process and ensuring its sustainability. A more efficient production process could yield as much or even more output (i.e., animal feed) with even lower production costs and lower energy consumption. Herein, a data envelopment analysis (DEA) was undertaken considering the monthly input–output data of two producers of animal feed obtained from food waste in Japan to analyze the monthly production efficiency in converting food waste into animal feed. The DEA is a non-parametric method that identifies the shape of the production frontier based on observed input–output combinations; moreover, it helps to measure the efficiency score of each decision-making unit (DMU) based on the relative distance between the identified frontier and the DMUs (Banker et al. 1984; Charnes et al. 1978). Specifically, we first collected monthly input and output data from January 2017 to July 2020 from two producers of dry animal feed obtained from food waste in Japan: “producer-A” (treating food waste from manufacturing and wholesaling) and “producer-B” (treating food waste from retail and service). Thereafter, by applying the slacks-based measure (SBM) model with fixed inputs in the DEA framework considering each of the two monthly time-series datasets, three relative production efficiency scores (i.e., technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE)) were estimated for each company, monthly. In addition, we estimated the slack proportion (SP) for each of the three inputs (electricity, heavy oil, and diesel fuel consumptions) in order to identify the causes of inefficiency considering the monthly production activities of each company. This study primarily aimed to discuss specific ways to improve the efficiency of converting food waste into animal feed by quantifying the inefficiencies and identifying their causes. The empirical results of this study could contribute toward the widespread use of food waste as animal feed, not only in Japan but also globally.

Literature review

A number of studies have discussed food waste issues in recent years using various approaches and covering various countries. Several studies provided surveys and reports on the amount of food waste and disposal methods in various countries based on statistical data and prevailing studies. Halloran et al. (2014) investigated food waste reduction efforts in Denmark and concluded that multi-stakeholder collaborations are crucial for arriving at sustainable solutions for reducing food waste. Parry et al. (2015) provided case studies for food loss and waste policy practices in Japan and the United Kingdom (UK). According to their study, food waste in the food industry has decreased in Japan; however, food waste at the consumer stage has remained unchanged over recent years. Liu et al. (2016) analyzed the food waste trend in Japan during 1960–2012 and summarized the status of food waste in the Japanese food supply chain in 2011. They reported that there was almost no potential for further reduction in food waste from the food manufacturing industry, which has primarily been recycled through animal feed and fertilizer; however, great potential exists in reducing food waste from other food industries, especially the food service industry. These existing studies show that food waste is a severe problem in many countries and that there is potential to recycle large quantities of food waste in each country.

The life cycle assessment (LCA) approach is often used to evaluate the environmental performance of food waste treatment methods. Lee et al. (2007) employed the LCA approach to estimate changes in the environmental impacts of food waste treatment systems (landfills, incineration, composting, and feed manufacturing) in Seoul during 1997–2005; their empirical analysis revealed that landfills primarily contributed to human toxicity and global warming. Kim and Kim (2010) evaluated feed manufacturing including dry feeding, wet feeding, composting, and landfilling for food waste disposal options considering lifecycle CO2 emissions; their empirical results indicated that dry feeding had the lowest lifecycle CO2 emissions per ton of food waste. Takata et al. (2012) employed the LCA and life cycle cost (LCC) approaches to evaluate the environmental and economic efficiency of the five food recycling facilities (i.e., machine integrated compost, windrow compost, liquid feed, dry feed, and bio-gasification) in Japan; they found that dry feed facilities had low total GHG emissions due to a high substitution effect, and they had high running costs due to low revenues obtained from food collection fees. Moul et al. (2018) assessed eight food waste disposal options for UK
Therefore, several studies were conducted to improve the produced animal feed is an issue that must be overcome. In addition to safety concerns, the poor quality of the produced animal feed is an issue that must be overcome. These studies clearly showed that conversion of food waste to animal feed was environmentally superior to other treatment methods.

Except for Japan and Korea, the conversion of food waste into animal feed is hardly tackled in other countries due to safety issues (zu Ermgassen et al., 2016). However, several studies investigated the possibility of its widespread use in the EU, the United States (US), and other countries, focusing on its favorable environmental performance. Sugiu et al. (2009) surveyed and introduced the entire process from collection of food waste to its final production and sale as eco-feed in Japan; they also reported on specific preventive measures against bovine spongiform encephalopathy in the production of eco-feed in Japan. Cheng and Lo (2016) investigated the market demand, technical viability, feed quality, regulatory hurdles, and potential contribution to examine the feasibility of converting food waste into fish feed in Hong Kong; the results showed that significant quantities of food waste could be recycled by converting it into fish feed due to the enormous demand from feed factories in mainland China. The conversion of food waste into animal feed in Japan and Korea was reviewed by zu Ermgassen et al. (2016) to quantify the potential of food waste for replacing conventional animal feed and reducing the environmental impact of meat production in EU. According to zu Ermgassen et al. (2016), recycled animal feed is attractive to the EU because of its low cost and low environmental impact; however, additional efforts are needed to address consumer and farmer concerns about food safety and disease control before it is widely adopted. Salemdeeb et al. (2017) investigated the potential benefits of diverting food waste toward pig feed in the UK; they employed the LCA approach to compare the environmental and health impacts of four technologies for food waste processing (wet pig feed and dry pig feed in South Korea; and anaerobic digestion and composting in UK). They concluded that the use of food waste as pig feed could offer environmental and public health benefits in the UK with the support of policy makers. Truong et al. (2019) conducted an extensive literature review focusing on the conversion of food waste into animal feed in the US food supply chain; according to their survey, utilizing food waste as animal feed (especially for chickens) in California could help reduce food waste in landfills while providing nutrition to animals and subsequently humans. Considering these studies, it is desirable to further promote the use of food waste as animal feed in various countries because it has excellent environmental and economic benefits; although, safety is an issue.

In addition to safety concerns, the poor quality of the produced animal feed is an issue that must be overcome. Therefore, several studies were conducted to improve the

productivity of animal feed obtained from food waste. Westendorf et al. (1998) compared pigs raised on cafeteria food waste with those raised on corn or soybean meal considering growth, meat quality, and dietary digestibility; the results indicated that food waste has nutritional value and could be useful in swine diets. Khounsaknalath et al. (2010) compared the growth performance and taste of beef cattle raised on eco-feed with that of beef cattle raised on normal feed; their results revealed that eco-feed had no negative effect on the animal growth and taste of beef. In Ruttananvat et al. (2011), Ruttananvat and Yamauchi (2012), and Takahashi et al. (2012), the growth performance of chickens and pigs raised on eco-feed was investigated to determine the optimal feeding level.

The aforementioned studies evaluated the environmental and economic performance of processing food waste into animal feed, assessed the applicability of its introduction in various countries considering safety, and contributed toward helping enhance the quality of animal feed. However, these studies did not provide quantitative measurements of the inefficiencies or the sources of such inefficiencies in the process of converting food waste into animal feed. This deficiency must be compensated to enhance the efficiency of the production process and to strengthen its sustainability. Hence, we applied the DEA-based monthly production efficiency evaluation framework proposed by Kagawa et al. (2013) and Eguchi et al. (2015) to develop a novel framework to evaluate the monthly production efficiency of food waste recycling plants and identify the respective potential for improvement in the utilization efficiency of multiple inputs.1

This study has two novel aspects. (1) It is the first to focus on the monthly production efficiency in the process of converting food waste into animal feed. Previous studies (Kim and Kim 2010; Lee et al. 2007; Moult et al. 2018; Takata et al. 2012) compared the environmental and economic efficiency of converting food waste into animal feed with other treatment methods; however, no study evaluated the efficiency of the conversion process on a monthly basis. (2) It provides a framework for quantifying the potential

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1 Kagawa et al. (2013) and Eguchi et al. (2015) employed the DEA to evaluate the efficiency of the production of biodiesel. Kagawa et al. (2013) applied the DEA to monthly input and output data of a plant producing biodiesel from waste cooking oil to evaluate the monthly production efficiency. They found that the monthly efficiencies of the biodiesel production process were inconsistent, given the differences in the estimated production efficiencies for each month. Additionally, they demonstrated that an improvement in production efficiency led to a reduction in the biodiesel production cost. Eguchi et al. (2015) developed the work done in Kagawa et al. (2013) to consider life cycle CO₂ emissions. Their empirical studies revealed that improvements in production efficiency helped reduce not only production costs but also lifecycle CO₂ emissions.
for improvements in the utilization efficiency of multiple inputs during monthly production. The monthly production efficiency evaluation frameworks of Kagawa et al. (2013) and Eguchi et al. (2015) are able to estimate the potential for reducing production costs and CO₂ emissions through efficiency improvements; however, they are unable to quantify the potential for improvements in the utilization efficiency of the respective inputs. Furthermore, our proposed evaluation framework can address cases where there are “fixed inputs” (i.e., inputs that are not desired to be reduced) in a producer’s production process. Thus, it can be applied, for example, to evaluate the production efficiency of a biodiesel recycler that uses waste cooking oil as an input, the collection of which is not likely to decrease.

**Methodology**

The DEA is a mathematical approach used for evaluating relative efficiency among different DMUs. The DEA was originally proposed by Charnes et al. (1978); thereafter, it was used extensively in operations research, management, and economics (Emrouznejad and Yang 2018; Mahmoudi et al. 2020; Sueyoshi et al. 2017; Zhou et al. 2018). Tone (2001) developed the SBM model that quantifies the input excesses and the output shortfalls of DMUs. However, in some cases, there are some fixed inputs, which a decision maker is not allowed/willing to reduce (Banker and Morey 1986; Esmaeili and Rostamy-Malkhalifeh 2017; Takayabu 2020). To handle fixed inputs, Esmaeili and Rostamy-Malkhalifeh (2017) extended the SBM model.

Following Esmaeili and Rostamy-Malkhalifeh (2017), the SBM model with fixed inputs can be expressed as follows:

\[
\text{Minimize} \quad T E_n = \frac{1 - (1/J) \sum_{j=1}^{J} s_{jn}^x / x_{jn}}{1 - (1/K) \sum_{k=1}^{K} s_{kn}^y / y_{kn}}
\]

subject to \( \mathbf{x}_n = \mathbf{X} \lambda + \mathbf{s}^x \)

\[
\mathbf{x}_{n}^{\text{fixed}} = \mathbf{X}^{\text{fixed}} \lambda + \mathbf{s}^{\text{fixed}}
\]

\[
\mathbf{y}_n = \mathbf{Y} \lambda - \mathbf{s}^y
\]

\[
\lambda \geq 0, \mathbf{s}^x \geq 0, \mathbf{s}^{\text{fixed}} \geq 0, \mathbf{s}^y \geq 0
\]

where \( T E_n \) is the technical efficiency score of DMU \( n \); \( J \) represents the number of inputs; \( K \) represents the number of outputs; \( s_{jn}^x \) and \( s_{kn}^y \) denote slacks of the \( j \)th input and \( k \)th output for DMU \( n \), respectively; \( x_{jn} \) and \( y_{kn} \) are the \( j \)th input and \( k \)th output for DMU \( n \), respectively; \( x_{n}^{\text{fixed}}, \mathbf{x}_n^{\text{fixed}}, \) and \( \mathbf{y}_n \) are the input, fixed input, and output vectors for DMU \( n \), respectively; \( \mathbf{X}, \mathbf{X}^{\text{fixed}}, \) and \( \mathbf{Y} \) are the input matrix, fixed input matrix, and output matrix, respectively; and \( \lambda, s^x, s^{\text{fixed}}, \) and \( s^y \) are the intensity weight vector, input slack vector, fixed input slack vector, and output slack vector, respectively. \( \lambda, s^x, s^{\text{fixed}}, \) and \( s^y \) were endogenously determined by solving the above fractional programming problem (FPP).

\( T E_n \) ranged between 0 and 1 (\( 0 < T E_n \leq 1 \)), while \( T E_n = 1 \) indicated that DMU \( n \) was efficient. Conversely, a lower efficiency score indicated greater inefficiency. The fractional programming problem (1) is based on the constant returns to scale (CRS) assumption; moreover, the problem can be extended into the variable returns to scale (VRS) model by adding the constraint \( \sum_{n=1}^{N} \lambda_n = 1 \) to FPP (1), where \( N \) is the number of DMUs. By solving the VRS SBM model, we could obtain a pure technical efficiency score of DMU \( (P T E_n) \).

According to Banker et al. (1984) and Shi et al. (2010), \( T E_n \) and \( P T E_n \) have the following relationship:

\[
T E_n \leq P T E_n
\]

In addition, the scale efficiency of DMU \( n \) (\( S E_n \)) could be calculated as follows:

\[
S E_n = \frac{T E_n}{P T E_n}
\]

\( S E_n \) also ranged between 0 and 1; moreover, a lower value of the scale efficiency indicated a more inefficient production scale. In other words, DMUs with a lower scale efficiency operate at a considerably small/large production scale; furthermore, they need to control the production scale to improve scale efficiency. Equation (3) could be rewritten as follows:

\[
T E_n = P T E_n \times S E_n
\]

Equation (4) indicates that the technical efficiency could be decomposed into two terms: pure technical efficiency and scale efficiency. The overall technical efficiency of DMUs could be improved by improving the pure technical efficiency and scale efficiency (Shi et al. 2010).

Fukuyama (2001) and Shi et al. (2010) used an additional DEA model called the non-increasing returns to scale (NIRS) model to observe the properties of a DMU including efficiency and scale efficiency (Shi et al. 2010).

Fukuyama (2001) and Shi et al. (2010) used an additional DEA model called the non-increasing returns to scale (NIRS) model to observe the properties of a DMU including efficiency and scale efficiency (Shi et al. 2010).
\[
\begin{align*}
    x^\text{fixed}_n &= X^\text{fixed} + s^\text{fixed} \\
    y_n &= Y - s^n
\end{align*}
\]  
\( (5) \)

\[
\sum_{n=1}^{N} \lambda_n \leq 1
\]

\( \lambda \geq 0, s^i \geq 0, s^\text{fixed} \geq 0, s^n \geq 0 \)

where \( \text{NTE}_n \) is the NIRS technical efficiency of DMU \( n \). Following Shi et al. (2010), this study defines a DMU’s nature of returns to scale (RTS) as follows:

If \( \text{PTE}_n > \text{NTE}_n = \text{TE}_n \), a DMU’s nature of RTS is IRS. This implies that if the inputs were increased by \( t \) times, then the outputs would increase by \( > t \) times. Therefore, the scale efficiency of such DMUs could be improved by expanding the production scale.

If \( \text{PTE}_n = \text{NTE}_n > \text{TE}_n \), a DMU’s nature of RTS is DRS. This implies that if the inputs were increased by \( t \) times, then the outputs would increase by \( < t \) times. Therefore, the scale efficiency of such DMUs could be improved by contracting the production scale.

If \( \text{PTE}_n = \text{NTE}_n = \text{TE}_n \), a DMU’s nature of RTS is CRS. This implies that if the inputs were increased by \( t \) times, then the outputs would increase by \( t \) times. Therefore, the production scale of such DMUs is appropriate (i.e., \( \text{SE}_n = 1 \)).

For an empirical analysis, this study considered three inputs (electricity, heavy oil, and diesel oil consumption), one fixed input (collected food waste), and one output (animal feed production) for 43 months (January 2017 to July 2020). Thus, the number of inputs is 3 (\( J = 3 \)), the number of outputs is 1 (\( K = 1 \)), and the number of DMUs is 43 (\( N = 43 \)). Here, food waste was considered as a fixed input for two reasons: First, the amount of food waste collected by animal feed producers should not be reduced to establish a recycling-oriented society in Japan (MAFF 2021). Second, the animal feed producers are unwilling to reduce the amount of food waste collection.

Specifically, in our empirical study, we evaluated the monthly production efficiency of two animal feed producers at different production frontiers. This is because the food waste collection channels and equipment used in the production process of these two producers varied (see “6” section). Solving FPP (1), we could obtain a slack value for each input and output under CRS assumption. The obtained slack values indicated a potential reduction (expansion) in the input (output); higher slack values indicated greater inefficiency. However, DMUs with a higher input and output tended to have higher slack values. Eguchi et al. (2021) and Nakaishi et al. (2021) normalized slack values by calculating the SP. Following Eguchi et al. (2021) and Nakaishi et al. (2021), SP was calculated as follows:

\[
\begin{align*}
    SP_{jn}^x &= \frac{s_{jn}^x}{x_{jn}} \\
    SP_{jn}^y &= \frac{s_{jn}^y}{y_{jn}}
\end{align*}
\]  
\( (6) \)

where \( SP_{jn}^x \) and \( SP_{jn}^y \) denote the SP value of \( j \)th input and \( k \)th output for DMU \( n \), respectively. SP could be regarded as the technology improvement potential of the prevailing technology level of each input and output (Eguchi et al. 2021; Nakaishi et al. 2021). Note that the SP ranges from 0 to 1; moreover, a higher SP value indicates greater inefficiency.

### Data

Here, the monthly input (electricity (kWh), heavy oil (L), and food waste consumption (t)) and output (animal feed production (t)) data from January 2017 to July 2020 collected from two manufacturers (i.e., producer-A and producer-B) producing animal feed from food waste in Japan were adapted to the DEA framework described above. Figure 1 illustrates the production flow of the animal feed obtained from food waste for the two producers. Herein, the food waste suppliers of each producer differed. In particular, producer-A treated business food waste from manufacturing and wholesaling, while producer-B treated business food waste from retail and service. In most cases, business food waste from retail and service contains more

\footnote{According to the MAFF (2021), Japan’s “Fundamental Plan for Establishing a Sound Material-Cycle Society” sets out the following priority guidelines for food waste reduction: (1) control of generation, (2) reuse, (3) recycling, (4) heat recovery, and (5) proper disposal. The production of animal feed from food waste is a preferred measure to reduce food waste under guidelines (2) or (3).}

\footnote{The monthly input and output data for the empirical analysis were collected from two leading Japanese manufacturers of food waste-based animal feed. The data provided were based on quantitative records of daily inputs and outputs at each manufacturer. The inputs and outputs used in the empirical analysis were selected based on our on-site investigation of the manufacturing process and the opinions of experts engaged in the manufacturing process there.}
water and impurities than that from manufacturing and wholesaling; moreover, its nutritional composition is more unstable. Therefore, business food waste from retail and service is more difficult to convert into animal feed; moreover, in Japan, the number of producers treating business food waste from retail and service is fewer than those treating business food waste from manufacturing and wholesaling (MAFF 2020b). Conversely, each of the two producers produced dried animal feed.5 Business food waste supplied by each food waste supplier was collected by each producer using trucks; moreover, diesel oil was consumed at this time. Thereafter, the collected food waste was separated from the packaging containers, heat-treated, and converted into feed through a drying process.6 Heavy oil was consumed in the drying process while electricity was consumed in the other processes.

Table 1 shows the descriptive statistics of the input–output data used here. In Table 1, the average values of electricity consumption and heavy oil consumption differed between producer-A and producer-B; this mainly occurred due to the difference in the equipment used in the drying process. Additionally, the scale of producer-A was larger than that of producer-B; hence, the two producers also demonstrated a huge difference in their average electricity consumption. Even though the average food waste collection by the two producers differed insignificantly, the average animal feed production differed significantly due to the difference in the food waste collection channels between the two producers.

5 Animal feed from food waste could also be produced by drying, processing in liquid form, or silaging. See Sugiura et al. (2009) for the differences in production methods.

6 The equipment used in the drying process differed between the two companies: producer-A utilized the indirect steam drying method, and producer-B, the vacuum drying method.
Business food waste from retail and service contains more water and impurities than that from manufacturing and wholesaling; thus, the weight of the former decreases more than the latter after the drying process.

To better understand the different properties of the food waste treated by each producer, the monthly “quality of food waste (QFW)” could be calculated for each producer by dividing the animal feed production by the food waste collection. The QFW value is generally determined by the moisture and impurity content in the collected food waste. Specifically, if the collected food waste contains excessive moisture or impurities, the QFW value is likely to be low.\(^7\) In fact, the average QFW value for producers A and B was 0.66 and 0.13, respectively. Considering this difference in QFW values, we could confirm that the food waste collected by producer-B contained more water and impurities than that collected by producer-A.

Additionally, we could confirm the difference in the food waste collection channels between producers A and B by comparing the difference in the coefficient of variation (CV) of each input–output by month. The CV was calculated by dividing the standard deviation of each input–output by each average value as in Table 1. The calculated CV of producer-B (0.15 for the food waste collection; 0.15 for the animal feed production) was higher than that of producer-A (0.07 for the food waste collection; 0.10 for the animal feed production). This difference in CV values between the two producers implied that producer-A collected food waste more stably than producer-B. In fact, producer-A, which treated business food waste from manufacturing and wholesaling, collected from 15 large-scale bakery and confectionery factories, thus easily maintaining a stable collection volume. Conversely, producer-B, which treated business food waste from retail and service, collected from approximately 200 small- and medium-sized restaurants and retailers; hence, a stable amount of food waste collection could not always be expected.

Results and discussion

Technical, pure technical, and scale efficiencies

Table 2 shows the technical efficiency (TE), pure technical efficiency (PTE), scale efficiency (SE), and RTS by month for each producer. From Table 2, it is clear that producers A and B had 8 and 2 technically efficient (i.e., TE = 1) months, respectively, during the analysis period. In other words, there were 35 and 41 months of inefficient production activities considering producers A and B, respectively. The average TE for producers A and B was 0.85 and 0.73, respectively; this indicates that the monthly production efficiency of producer-B was less consistent than that of producer-A.

The PTE is an efficiency score purely for production technology without considering the effect of production scale. Table 2 shows that 18 months in producer-A and 6 months in producer-B demonstrated pure technical efficiency (i.e., PTE = 1) during the analysis period. Note that the PTE had been improving year by year for each producer, respectively.\(^8\) The average PTE for producer-A and producer-B in FY2018 was 0.89 and 0.75, respectively, and in FY2020, it was 0.98 and 0.96, respectively, being considerably higher than that of the two previous years. This could be attributed to the operational management of both companies for the production efficiency improvements. In fact, the plant manager of producer-A actively worked toward improving production efficiency by adopting the environmental management system promoted by the Ministry of the Environment (i.e., Eco-Action 21); hence, the successful outcome was definitely reflected in the PTE score.

SE indicates the monthly efficiency of the production scale, where SE = 1 indicates an optimal production scale. The average SE for producer-A was 0.93, and for producer-B, 0.90, implying that both producers had inefficiencies considering the scale of their production. The average SE of producer-B was lower than that of producer-A. Additionally, the CV of the SE in producer-B (1.22) was greater than that of SE in producer-A (1.15). The differences in the mean and the CV of the SE between the two producers indicated that producer-B demonstrated greater variation in the monthly production scale and had greater scale inefficiencies. This is because, as described in the “6” section, producer-B collected food waste mainly from restaurants and retail industries; moreover, it was difficult to obtain food waste constantly. Furthermore, it is noteworthy that since April 2020 when the COVID-19 infection began spreading, only the SE scores for producer-B had fallen significantly, while the PTE was maintained at a high level. In Japan, a “state of emergency” was declared April 2020 onward due to the COVID-19 pandemic; hence, the amount of food waste decreased as a result of restrictions on visiting restaurants. Therefore, producer-B, which mainly collected food

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\(^7\) It should be noted that the QFW value is slightly affected by the performance of the equipment in addition to the moisture and impurity content in the collected food waste. Specifically, when separating food waste from impurities, machines may incorrectly remove a small amount of food waste that could be used as animal feed.

\(^8\) Note that the “improving” of efficiency here includes both efficiency change and technological change. In the general DEA context, time series changes in efficiency are decomposed into efficiency changes and technology changes with the DEA-type Malmquist index (Färe et al., 1992). However, this decomposition requires that the input–output data used are balanced panel data. In other words, our empirical analysis based on monthly time series data does not allow us to identify the sources of time series changes in efficiency. This is one of the limitations of our study and can be overcome by extending the data used to monthly balanced panel data.
| Year. Month | Producer-A | | | Producer-B | | |
| --- | --- | --- | --- | --- | --- | --- |
| | TE | PTE | SE | RTS | TE | PTE | SE | RTS |
| 2017.01 | 0.720 | 0.867 | 0.831 | IRS | 0.667 | 0.765 | 0.873 | IRS |
| 2017.02 | 0.847 | 1.000 | 0.847 | IRS | 0.882 | 0.887 | 0.995 | DRS |
| 2017.03 | 0.813 | 0.862 | 0.944 | IRS | 1.000 | 1.000 | 1.000 | CRS |
| 2017.04 | 0.767 | 1.000 | 0.767 | IRS | 0.851 | 0.856 | 0.993 | DRS |
| 2017.05 | 0.745 | 0.833 | 0.894 | IRS | 0.646 | 0.734 | 0.881 | IRS |
| 2017.06 | 0.846 | 0.871 | 0.972 | DRS | 0.851 | 1.000 | 0.851 | IRS |
| 2017.07 | 0.778 | 0.779 | 0.998 | IRS | 0.679 | 0.730 | 0.931 | IRS |
| 2017.08 | 1.000 | 1.000 | 1.000 | CRS | 0.675 | 0.773 | 0.873 | IRS |
| 2017.09 | 0.843 | 0.866 | 0.974 | IRS | 0.762 | 0.772 | 0.987 | IRS |
| 2017.10 | 1.000 | 1.000 | 1.000 | CRS | 0.740 | 0.749 | 0.988 | DRS |
| 2017.11 | 0.884 | 1.000 | 0.884 | IRS | 0.696 | 0.756 | 0.921 | IRS |
| 2017.12 | 0.767 | 0.788 | 0.973 | IRS | 0.833 | 0.861 | 0.968 | DRS |
| 2018.01 | 0.685 | 0.731 | 0.937 | IRS | 0.707 | 0.726 | 0.973 | IRS |
| 2018.02 | 0.775 | 0.802 | 0.967 | IRS | 0.746 | 0.782 | 0.955 | IRS |
| 2018.03 | 0.785 | 0.794 | 0.988 | DRS | 0.748 | 0.750 | 0.997 | DRS |
| 2018.04 | 0.819 | 0.828 | 0.988 | DRS | 0.753 | 0.770 | 0.977 | IRS |
| 2018.05 | 0.855 | 0.859 | 0.995 | DRS | 0.681 | 0.684 | 0.997 | DRS |
| 2018.06 | 0.727 | 0.798 | 0.912 | IRS | 0.650 | 0.684 | 0.950 | IRS |
| 2018.07 | 0.686 | 0.689 | 0.995 | DRS | 0.623 | 0.716 | 0.870 | IRS |
| 2018.08 | 0.870 | 0.917 | 0.948 | IRS | 0.637 | 0.749 | 0.851 | IRS |
| 2018.09 | 0.781 | 1.000 | 0.781 | IRS | 0.621 | 0.750 | 0.829 | IRS |
| 2018.10 | 0.842 | 0.845 | 0.997 | DRS | 0.741 | 0.797 | 0.930 | IRS |
| 2018.11 | 0.899 | 0.910 | 0.988 | IRS | 0.764 | 0.806 | 0.948 | IRS |
| 2018.12 | 0.986 | 1.000 | 0.986 | DRS | 0.754 | 0.757 | 0.996 | IRS |
| 2019.01 | 1.000 | 1.000 | 1.000 | CRS | 0.714 | 0.754 | 0.947 | IRS |
| 2019.02 | 1.000 | 1.000 | 1.000 | CRS | 0.689 | 0.776 | 0.888 | IRS |
| 2019.03 | 0.789 | 0.796 | 0.991 | DRS | 0.747 | 0.818 | 0.913 | IRS |
| 2019.04 | 0.834 | 0.930 | 0.896 | IRS | 0.653 | 0.789 | 0.828 | IRS |
| 2019.05 | 0.886 | 1.000 | 0.886 | IRS | 0.743 | 0.780 | 0.952 | IRS |
| 2019.06 | 0.869 | 1.000 | 0.869 | IRS | 0.773 | 0.824 | 0.938 | IRS |
| 2019.07 | 0.967 | 0.974 | 0.993 | DRS | 0.733 | 0.807 | 0.908 | IRS |
| 2019.08 | 0.881 | 0.881 | 1.000 | CRS | 0.761 | 0.838 | 0.908 | IRS |
| 2019.09 | 0.868 | 0.868 | 1.000 | CRS | 0.804 | 0.832 | 0.966 | IRS |
| 2019.10 | 0.652 | 0.821 | 0.794 | IRS | 0.779 | 0.787 | 0.990 | IRS |
| 2019.11 | 0.762 | 1.000 | 0.762 | IRS | 0.729 | 0.806 | 0.905 | IRS |
| 2019.12 | 0.909 | 0.963 | 0.943 | IRS | 0.660 | 0.761 | 0.867 | IRS |
| 2020.01 | 0.833 | 1.000 | 0.833 | IRS | 0.773 | 0.809 | 0.956 | IRS |
| 2020.02 | 0.792 | 1.000 | 0.792 | IRS | 0.692 | 0.800 | 0.864 | IRS |
| 2020.03 | 1.000 | 1.000 | 1.000 | CRS | 1.000 | 1.000 | 1.000 | CRS |
| 2020.04 | 1.000 | 1.000 | 1.000 | CRS | 0.574 | 1.000 | 0.574 | IRS |
| 2020.05 | 1.000 | 1.000 | 1.000 | CRS | 0.502 | 1.000 | 0.502 | IRS |
| 2020.06 | 1.000 | 1.000 | 1.000 | CRS | 0.611 | 1.000 | 0.611 | IRS |
| 2020.07 | 0.813 | 0.903 | 0.901 | IRS | 0.664 | 0.858 | 0.773 | IRS |
| Mean | 0.851 | 0.911 | 0.934 | | 0.728 | 0.811 | 0.897 | |
| Max | 1.000 | 1.000 | 1.000 | | 1.000 | 1.000 | 1.000 | |
| Min | 0.652 | 0.689 | 0.947 | | 0.502 | 0.684 | 0.734 | |
| SD | 0.098 | 0.091 | 0.076 | | 0.096 | 0.087 | 0.109 | |
waste from food retailers and restaurants, was unable to collect a stable volume of food waste. In contrast, the SE of producer-A remained high after April 2020, indicating that producer-A was unaffected by COVID-19. This is because food manufacturers were the main suppliers of food waste for producer-A; hence, they were able to stably collect food waste during the COVID-19 outbreak.

Table 2 also provides the nature of the RTS for each producer, monthly. In the months where the nature of the RTS was an IRS, the production scale needed to be increased because it was considerably small to obtain economies of scale (Shi et al. 2010). Conversely, in the months when the nature of the RTS was a DRS, the production scale was considerably large, with the occurrence of congestion; hence, the production scale required a reduction (Shi et al. 2010). As per Table 2, producers A and B were characterized by 24 and 35 months, respectively, with an IRS, implying that both producers could have gained economies of scale by expanding their production over many months. In particular, producer-B was characterized by a greater number of months with an IRS than producer-A due to the instability in food waste collection as mentioned above. Therefore, expanding the production scale of producers treating food waste from retail and service, such as producer-B, is more important toward improving production efficiency.

Figure 2 shows a scatter plot of the animal feed production and the SE; for both producers, it can be observed that the SE tended to be higher at a larger production scale. Consequently, the TE also tended to increase with an expansion in the production scale (see Fig. 5a in the Appendix). Therefore, expanding the production scale is critical toward improving the efficiency in producing animal feed from food waste. A comparison of the coefficients of determination for each producer as in Fig. 2 also suggests that expanding the production scale of producers such as producer-B is particularly important for improving production efficiency.

### Slack proportion

The SP, calculated in Eqs. (6) and (7), indicates the technology improvement potential of the prevailing technology level

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9 In the specific production process, the collected food waste was converted into animal feed in the drying machine after removing impurities. The amount of heavy oil and electricity consumed to run a unit of the drying machine was constant, regardless of the amount of food waste processed by the machine (i.e., capacity utilization rate). Therefore, the producers could benefit from economies of scale by fully utilizing the drying machine’s capacity. Conversely, when the amount of food waste to be processed is low compared to the maximum capacity of the drying machine, it leads to the wastage of fuel oil and electricity.

10 Note that PTE does not have a correlation with production scale (see Fig. 5b).
of each input and output (Eguchi et al., 2021). In other words, the magnitude of the SP could be directly interpreted as the magnitude of inefficiency, considering a specific input and output. Figure 3 summarizes the monthly SP with respect to each of the three inputs (i.e., electricity, heavy oil, and diesel oil consumption) for each producer.11 Going ahead, the plant managers of each producer could refer to Fig. 3 to implement improvements for enhancing production efficiency.

Figure 3 shows that in producer-A, the average SP value was the highest (i.e., inefficient) for heavy oil, while it also had high variability. This indicates that producer-A had the greatest potential for improvements in the utilization efficiency of heavy oil. In particular, efficiency, considering the use of heavy oil, could be improved by introducing more fuel-efficient drying equipment. In fact, producer-A introduced more fuel-efficient drying equipment in 2019; the effectiveness is observable in Fig. 3, where the SP value considering heavy oil is clearly lower (i.e., more efficient) since 2019. Figure 3 also shows that the average SP value was the lowest (i.e., efficient) for diesel oil; moreover, its variability was the smallest in producer-A. This is because producer-A, which treated business food waste from manufacturing and wholesaling, could easily estimate in advance the amount of food waste and its time of occurrence considering the food manufacturers; hence, it could flexibly adjust the collection route and number of trucks required for collection.

In contrast, in producer-B, the average SP value was the lowest (i.e., efficient) for heavy oil and the highest (i.e., inefficient) for diesel oil. In other words, producer-B had a high potential for improvement in the use of diesel oil in the food waste collection process. This is because producer-B, which treated business food waste from retail and service, could not flexibly adjust collection routes and the number of trucks required as it is difficult to predict in advance the amount of food waste that could be collected from retailers and restaurants. Furthermore, considering Fig. 3, we could confirm that the SP value for diesel oil used in producer-B was particularly high after April 2020. Although statistical causality has not been verified, this suggests that the COVID-19 pandemic has disrupted the supply of food waste from restaurants to producer-B and decreased the food waste collection efficiency by diesel trucks. It is also clear from Fig. 3 that the SP values for heavy oil and electricity use increased after April 2020, similar to the case for diesel oil. Normally, it is difficult for producers to flexibly change the equipment size used in response to changes in the amount of food waste collected in a short time period. The amount of food waste that collected by producer-B decreased drastically during the COVID-19 pandemic. The increased SP values imply a consequent decrease in the utilization efficiency of heavy oil and electricity (i.e., animal feed production per unit consumption) for producer-B.

As mentioned in the “6” section, the QFW value was mainly determined by the moisture content and impurities present. If the collected food waste is of low quality, a substantial amount of energy is required for removing impurities and for heating and drying. Therefore, we could assume that the QFW value significantly affects the monthly efficiency score and SP. Figure 4 shows the scatter plot of the monthly QFW and SP. Considering Fig. 4, the SP and QFW are negatively correlated for all inputs for each producer. In other words, an improvement in the QFW could lead to an improvement in efficiency for all inputs. Table 3 summarizes the results of the simple regression analysis considering the monthly QFW values for each producer as the independent variables and the monthly SP values for the input of each producer as the dependent variables. The results of the simple regression analysis in Table 3 demonstrate that a significant negative relationship exists between the QFW and all other SPs of the two producers, except for the SP considering heavy oil in producer-A. Furthermore, by comparing the magnitude of the parameters between the two producers, the QFW has a greater influence on each SP value for producer-B. In other words, for producers treating food waste from retail and service, such as producer-B, improving the QFW is particularly important toward improving the efficiency, considering the use of each input.12 An improvement in the QFW (i.e., a reduction in the moisture and impurity content) leads to an improved fuel efficiency of diesel trucks and reduced electricity and heavy oil consumption in the fractionation and drying processes.

**Conclusion and policy implication**

Here, the DEA was applied to the monthly input–output data of two food waste–based animal feed producers in Japan to quantify their production efficiency and identify the sources of inefficiency. Based on the results of estimated TE, producers A and B demonstrated 35 and 41 months of inefficient production activity, respectively; the monthly production efficiency for producer-B was less consistent than that of producer-A. The estimated SE and RTS values demonstrate that both producers had production inefficiencies related to scale, which could be improved by increasing the production

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11 We also calculated the SP for animal feed production using Eq. (7). However, all SP values equaled to zero; hence, they are not listed in Fig. 3.

12 Specifically, the QFW value for producer-B can be increased by the efforts of the food waste suppliers. For example, retailers and restaurants (i.e., suppliers) can help increase the QFW value of producer-B by separating food and combustible waste before collection. Producer-B (i.e., collectors) can also increase the QFW value by refusing to collect lower quality food waste, though this is socially undesirable.
### Monthly slack proportions for each producer

| Year. Month | Producer A |  | Producer B |  |
|-------------|------------|----------------|------------|----------------|
|             | Electricity | Heavy oil | Diesel oil | Electricity | Heavy oil | Diesel oil |
| 2017.01     | 0.32        | 0.37       | 0.15       | 0.47        | 0.27       | 0.26       |
| 2017.02     | 0.18        | 0.26       | 0.02       | 0.25        | 0.00       | 0.10       |
| 2017.03     | 0.21        | 0.28       | 0.07       | 0.00        | 0.00       | 0.00       |
| 2017.04     | 0.23        | 0.35       | 0.11       | 0.31        | 0.03       | 0.12       |
| 2017.05     | 0.25        | 0.37       | 0.14       | 0.40        | 0.28       | 0.38       |
| 2017.06     | 0.16        | 0.30       | 0.00       | 0.17        | 0.00       | 0.28       |
| 2017.07     | 0.25        | 0.33       | 0.09       | 0.38        | 0.22       | 0.37       |
| 2017.08     | 0.00        | 0.00       | 0.00       | 0.41        | 0.23       | 0.34       |
| 2017.09     | 0.17        | 0.28       | 0.02       | 0.30        | 0.07       | 0.34       |
| 2017.10     | 0.00        | 0.00       | 0.00       | 0.30        | 0.14       | 0.34       |
| 2017.11     | 0.08        | 0.26       | 0.00       | 0.35        | 0.18       | 0.38       |
| 2017.12     | 0.26        | 0.31       | 0.12       | 0.25        | 0.05       | 0.20       |
| 2018.01     | 0.32        | 0.44       | 0.18       | 0.40        | 0.17       | 0.31       |
| 2018.02     | 0.26        | 0.39       | 0.03       | 0.33        | 0.11       | 0.31       |
| 2018.03     | 0.26        | 0.37       | 0.02       | 0.31        | 0.16       | 0.29       |
| 2018.04     | 0.20        | 0.33       | 0.01       | 0.32        | 0.13       | 0.29       |
| 2018.05     | 0.16        | 0.26       | 0.01       | 0.33        | 0.24       | 0.39       |
| 2018.06     | 0.22        | 0.34       | 0.26       | 0.39        | 0.27       | 0.40       |
| 2018.07     | 0.33        | 0.39       | 0.23       | 0.38        | 0.31       | 0.45       |
| 2018.08     | 0.09        | 0.13       | 0.17       | 0.41        | 0.29       | 0.39       |
| 2018.09     | 0.18        | 0.21       | 0.27       | 0.35        | 0.29       | 0.50       |
| 2018.10     | 0.09        | 0.18       | 0.20       | 0.22        | 0.13       | 0.43       |
| 2018.11     | 0.08        | 0.11       | 0.12       | 0.16        | 0.17       | 0.38       |
| 2018.12     | 0.01        | 0.00       | 0.03       | 0.17        | 0.26       | 0.31       |
| 2019.01     | 0.00        | 0.00       | 0.00       | 0.22        | 0.30       | 0.34       |
| 2019.02     | 0.00        | 0.00       | 0.00       | 0.27        | 0.29       | 0.38       |
| 2019.03     | 0.17        | 0.24       | 0.23       | 0.20        | 0.19       | 0.37       |
| 2019.04     | 0.11        | 0.21       | 0.17       | 0.30        | 0.36       | 0.39       |
| 2019.05     | 0.04        | 0.16       | 0.15       | 0.19        | 0.21       | 0.38       |
| 2019.06     | 0.06        | 0.18       | 0.15       | 0.16        | 0.14       | 0.37       |
| 2019.07     | 0.01        | 0.09       | 0.00       | 0.22        | 0.22       | 0.37       |
| 2019.08     | 0.12        | 0.09       | 0.15       | 0.22        | 0.21       | 0.29       |
| 2019.09     | 0.14        | 0.15       | 0.10       | 0.09        | 0.16       | 0.33       |
| 2019.10     | 0.29        | 0.32       | 0.43       | 0.08        | 0.24       | 0.35       |
| 2019.11     | 0.25        | 0.26       | 0.20       | 0.15        | 0.30       | 0.37       |
| 2019.12     | 0.11        | 0.09       | 0.08       | 0.23        | 0.39       | 0.40       |
| 2020.01     | 0.19        | 0.15       | 0.16       | 0.12        | 0.28       | 0.29       |
| 2020.02     | 0.22        | 0.17       | 0.23       | 0.21        | 0.31       | 0.41       |
| 2020.03     | 0.00        | 0.00       | 0.00       | 0.00        | 0.00       | 0.00       |
| 2020.04     | 0.00        | 0.00       | 0.00       | 0.55        | 0.26       | 0.46       |
| 2020.05     | 0.00        | 0.00       | 0.00       | 0.57        | 0.41       | 0.51       |
| 2020.06     | 0.00        | 0.00       | 0.00       | 0.29        | 0.34       | 0.54       |
| 2020.07     | 0.22        | 0.21       | 0.14       | 0.24        | 0.30       | 0.47       |
| MEAN        | 0.15        | 0.20       | 0.10       | 0.27        | 0.21       | 0.34       |
| MAX         | 0.33        | 0.44       | 0.43       | 0.57        | 0.41       | 0.54       |
| MIN         | 0.00        | 0.00       | 0.00       | 0.00        | 0.00       | 0.00       |
| S.D.        | 0.10        | 0.13       | 0.10       | 0.13        | 0.11       | 0.11       |
scale. Producer-B demonstrated greater variation in the production scale and greater inefficiency considering the scale, mainly brought about by differences in the food waste collection channels. We also estimated the monthly SP for each producer to determine the level of inefficiency considering each of the three inputs. The results indicate that producer-A and producer-B have the potential to improve the utilization efficiency of heavy and diesel oil, respectively. A negative correlation was also identified between the QFW and the SP for each input considering each producer, indicating that an improvement in the QFW could help improve the efficiency considering all inputs. The QFW was particularly influential, considering an improvement in the efficiency of the three inputs of producer-B. Based on the findings of the empirical

Fig. 4 Scatter plot of QFW and slack proportions for each producer

Table 3  Estimates based on simple regression analysis

| Dependent variable | Producer-A | Producer-B |
|--------------------|------------|------------|
|                    | SP (electricity) | SP (heavy oil) | SP (diesel oil) | SP (electricity) | SP (heavy oil) | SP (diesel oil) |
| Constant           | 0.41***     | 0.35**     | 0.36***     | 0.54***     | 0.68***     | 0.92***     |
|                    | (0.00)      | (0.04)     | (0.00)      | (0.00)      | (0.00)      | (0.00)      |
| Coefficient (QFW)  | −0.4**      | −0.23      | −0.4**      | −2.05**     | −3.57***    | −4.42***    |
|                    | (0.04)      | (0.37)     | (0.03)      | (0.02)      | (0.00)      | (0.00)      |
| N                  | 43          | 43         | 43          | 43          | 43          | 43          |
| R squared          | 0.10        | 0.02       | 0.11        | 0.13        | 0.56        | 0.76        |

Numbers in parentheses indicate the $p$ value

*Significance at the 10% significance level; **significance at the 5% significance level; ***significance at the 1% significance level

scale. Producer-B demonstrated greater variation in the production scale and greater inefficiency considering the scale, mainly brought about by differences in the food waste collection channels. We also estimated the monthly SP for each producer to determine the level of inefficiency considering each of the three inputs. The results indicate that producer-A and producer-B have the potential to improve the utilization efficiency of heavy and diesel oil, respectively. A negative correlation was also identified between the QFW and the SP for each input considering each producer, indicating that an improvement in the QFW could help improve the efficiency considering all inputs. The QFW was particularly influential, considering an improvement in the efficiency of the three inputs of producer-B. Based on the findings of the empirical
analysis conducted, we can discuss a few policy implications for policy makers globally who are attempting to promote the use of food waste as animal feed, and for the Japanese government, which is working to increase the production volume of animal feed obtained from food waste.

As mentioned in the “I” section, the conversion of food waste into animal feed is currently not widely practiced, except in some East-Asian countries such as Japan and Korea, due to the risk of spreading diseases such as foot-and-mouth disease and African swine fever. However, the large amount of food waste during the consumption stage is a challenge for all developed countries, and many studies have examined the feasibility of introducing the production of animal feed to food waste in various countries as an effective solution, as shown in the “2” section; the first step toward this is sanitation management. The case studies for Japan and Korea have proved that a thorough heat treatment could help prevent the spread of diseases caused by food waste derived animal feed. Each country should first overcome sanitation issues by referring to the laws and technical systems adapted in Japan and Korea. In addition, government tax incentives and capital investment support for producers could increase animal feed production from food waste. Our empirical results suggested that producers processing commercial food waste from the retail and service industries had less uniform monthly production efficiency and were more sensitive to exogenous shocks (e.g., COVID-19) than producers processing commercial food waste from the manufacturing and wholesale industries. As our empirical results focused on two Japanese producers, it is not guaranteed that these results hold for every country. However, preferential support for producers such as producer-B is likely to be needed in most countries to increase food waste recycling rates through animal feed production.

In Japan, subsidies are provided to eco-feed producers based on its increased use to increase the recycling of food waste and expand the production of animal feed. Our empirical analysis proved that such a subsidy is reasonable, as it demonstrates that expanding the production scale helps improve the production efficiency of the feed-conversion process. The Japanese government also provides more subsidies to producers such as producer-B to increase the production of animal feed from business food waste from retail and service. Our study shows that expanding the production scale of producers treating food waste from retail and service is particularly important for improving their production efficiency. Therefore, the subsidy policy of the government to prioritize producers engaged in the conversion of business food waste from retail and service to animal feed is also considered to be reasonable.

Our empirical analysis showed that both producers had production inefficiencies; hence, the government needs to have additional policies to encourage the production of animal feed from food waste. The production efficiency of the feeding process can be enhanced not only by improving efficiency considering the production scale (i.e., SE), but also by improving the technical efficiency considering each input (i.e., SP) by improving the QFW. For example, retailers and restaurants could separate food waste and combustible waste before collection to improve their SP, considering the energy required to separate impurities (such as for producer-B). Optimization of food waste collection routes using information technology could also help improve the SP for diesel consumption, especially in producers such as producer-B. Additionally, incentives for food waste generators to choose recycling rather than incineration are also important to ensure the widespread use of food waste as animal feed. For example, if the government sets the collection cost of food waste by incineration companies to be costlier than that of food waste recycling companies, producers of food waste would naturally choose to recycle such waste.

Finally, although we did not test for statistical causality, the empirical results of this study suggest that the COVID-19 pandemic could have severely impacted producers (such as producer-B). The scale efficiency of producer-B has been extremely low since April 2020, suggesting that the company is not doing well financially. The government needs to urgently implement appropriate support policies not only for restaurants, but also for producers engaged in resource recycling further downstream in the supply chain, such as those producing animal feed from food waste.

This study had limitations considering that the input–output data was not available for numerous producers; it focused on the data only from two producers located in Japan. However, since 26 eco-feed producers existed in Japan as of 2020, additional data could be obtained for future studies. Furthermore, this study focused on production efficiency; however, it was unable to evaluate environmental efficiency or cost-efficiency. As the efficiency analysis framework using a DEA could also consider the environmental and economic aspects of production activities, the analysis could be further developed considering these perspectives. Furthermore, this study considered diesel fuel as the fourth input, following two existing studies (Kagawa et al. 2013; Eguchi et al. 2015). Once additional input data such as “size and number of collection trucks” and “drivers employed” can be collected, a network DEA model could be constructed to divide the production process into two stages: the “collection stage” and the “production stage.”
Appendix

Fig. 5 Scatter plot of monthly animal feed production and TE/PTE for each producer.

(a) TE

(b) PTE
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Author contribution Tomoaki Nakaishi: conceptualization; funding acquisition; data curation; resources; formal analysis; investigation; methodology; project administration; software; validation; visualization; writing — original draft; writing — review and editing. Hirotaka Takayabu: conceptualization; formal analysis; investigation; methodology; software; validation; visualization; writing — original draft; writing — review and editing.

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Data availability The data used in the empirical analysis was obtained directly from two typical animal feed from food waste producers in Japan. At their request, the data and company names cannot be disclosed without our approval.

Declarations

Ethical approval Not applicable.

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