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Assessing the efficiency of solid waste collection services in urban Ghana

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ABSTRACT

Whether private solid waste management companies are efficient in solid waste collection (SWC) has long dominated public discourse in Ghana. In many instances, such discourses are based on an empirical vacuum. This article seeks to provide the empirical basis on which discussions on SWC efficiency can be grounded. It examined the efficiency of resource inputs into SWC using the Data Envelopment Analysis. With cost and allocative efficiencies as model output, the value of total assets, number of trucks, number of collection containers, number of clients, and number of personnel deployed *were* set as input data, while the quantity of waste hauled and the amount of revenue generated was the output factors. The companies constituted the decision-making units (DMUs). The results showed that the average efficiency score for all DMUs was less than the 1.0 threshold for efficiency score. The results imply that the DMUs consistently operated inefficiently. We argue that the extent of inefficiencies provides the basis for stakeholders to re-examine the existing waste management architecture.

Introduction

It has become a commonly quoted environmental truism that of the many environmental challenges facing developing countries, poor solid waste management has emerged as the most critical (Godfrey et al., 2019; World Bank, 2021). Most environmental and policy decisions are largely devoted to how the technical issues and formal regulations guiding waste disposal can be enhanced (World Bank, 2021). For the past twenty years, many cities in Africa south of the Sahara have suffered a decline in improved solid waste disposal services driven by limited funding sources amid the increased population (UNEP, 2018). This situation reflects the waste management sector in Ghana, where unprecedented urbanization, lifestyle changes, shifting consumption habits, and accelerated economic growth have led to an overwhelming increase in solid waste generation and diversity in cities (Oteng-Ababio et al., 2017; Owusu-Sekyere, 2020). Studies have shown that apart from Accra and Kumasi, where formal waste collection systems are common, the collection rate in the remaining emerging cities is so low that they are not given much prominence under national statistics (Owusu et al., 2014; Owusu-Sekyere, 2016). The uncollected solid waste finds its way into drains and limits the flow of water through these drains. The stagnant water becomes good breeding sites for mosquitoes and other insects. The operational inefficiencies in emerging cities include but are not limited to the weak capacities of city authorities, lack of adequate funding, and weak policy enforcement (World Bank, 2021).

Ghana has adopted the private sector participation policy as an alternative to solid waste financing. Various researchers have adduced reasons for the policy adoption, including their ability to mobilize resources, reduce losses, expand the waste collection, and enhance service delivery (Baud, 2001; Helmsing, 2002; World Bank, 2015; World Bank, 2021). But whether the sector has been efficient in solid waste collection (SWC) has long dominated public discourse. For instance, some scholars have argued that despite introducing the private sector, waste management in Ghana has only seen marginal improvement (Peres, 2021; Oduro-Kwarteng and van Dijk, 2013). Other studies (see, for example, Oteng-Ababio, 2014; Vosuuri et al., 2023) have suggested that even though significant studies on the subject matter exist, the results from such studies are not rigorously placed with empirical evidence. They argue that since the private sector aims to maximize profit at a minimum cost through efficient resource use, studies must be conducted in African cities to examine how efficiently the private sector is improving the efficiency of waste management services. This article assesses the efficiency of solid waste collection services in selected communities in Ghana using Data Envelopment Analysis (DEA). The DEA was adopted because it is a non-parametric method that helps evaluate the relative efficiencies of decision-making units (DMUs) that perform similar tasks under varying conditions and for which inputs and output measurements are available (Goksen et al., 2015).

As a linear programming method, DEA constructs a frontier (non-parametric piecewise surface) over data to allow for the calculation

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of efficiencies relative to the frontier (surface) (Coelli et al., 2005). Although further modifications are considered to better capture the complex processes of solid waste management, DEA has become the dominant method for efficiency measurement in municipal solid waste management (MSWM) worldwide (Pombo and Taborda, 2006; Vaninsky, 2008). Multiple studies have been conducted on applying the DEA technique to analyze the efficiencies of solid waste management services worldwide. For instance, Simões et al. (2012) studied the efficiency of urban solid waste services using the DEA approach in Portugal. They established a significant relationship between solid waste service efficiencies and environmental factors. Similarly, Gallardo et al. (2010) estimated the efficiency of different waste collection systems in Spanish cities using DEA with fascinating results. Bosch et al. (2000) have also used the DEA model to analyze the technical and cost efficiencies of waste collection services in seventy-three municipalities of Catalonia.

In Ghana, application of DEA has been widely applied to analyze efficiencies in health, agricultural production, and non-governmental organizations (Charles et al., 2013; Mann et al., 2001; Marques and Simões, 2009; Benito et al., 2010; De Jaeger and Rogge, 2012). However, the use of DEA in efficiency measurement in solid waste management services is limited. In most studies, customer satisfaction measurement has often been used as an indicator of the efficient delivery of services. As opined by Huang et al. (2010), this approach often produces subjective results, as customers' values, perceptions and emotions influence the judgement of the quality of services. The critical challenge that limited the application of DEA in solid waste management is the lack of reliable data. This research considered a redefined approach for assessing the efficiency of door-to-door waste collection service using DEA since that is a more objective approach to assessing the efficiency of service delivery processes. The standard DEA model of Charnes, Cooper, and Rhodes (Charnes et al., 1978) under the assumption of convexity of inputs and outputs with a constant return to scale (CRC) is suitable for analyzing Decision Making Units (DMUs) that do not operate under a perfectly competitive environment (Bogetoft, 2000; Charles et al., 2013; Emrouznejad and Yang, 2018).

Consequently, using this model was appropriate as the selected study locations do not operate under perfect competition in the waste management sector in Ghana. This article contributes significantly to the waste management literature. First, it provides the empirical basis for grounded discussions on SWC efficiency. Secondly, it shows the right combination of resource inputs to deliver an expected output. This is significant as it helps both policymakers and private sector companies in the decision-making process on public sector management. The article is arranged as follows: the introduction is followed by the literature on Ghana's quest for efficient solid waste management systems. The methodology is subsequently presented, and the results and Discussions follow that. The conclusion and implications of the research for the waste management literature are finally presented.

The quest for efficient solid waste management systems in Ghana

Historical antecedents

Pursuing an efficient solid waste management system in Ghana has a historical antecedent. The quest started when the colonial authority realized the need to incorporate environmental protection into spatial planning practices. Rapid population growth and economic development were directly related to the volumes of waste being generated. With the increasing population mainly happening in Accra, the capital of the Gold Coast, there was the need for some institutional response to address the worsening sanitation challenge. The Accra City Council (ACC) was thus established in 1898 to keep the city clean. The first policy reforms on sanitation mimicked the duality of Accra's spatial planning - European Town and Native Town—the former hosted African elite and European expatriates while the latter was where the indigenous Africans lived. Typically, the native town was characterized by overcrowding, chaotic, and unsanitary environments, while the European town was well-laid with well-developed living conditions. By 1925, the European towns were served with household collection services, while the Native towns were served with public dustbins, which were collected by two pushcarts (Oteng-Ababio, 2014).

The reforms focused on waste collection, a fundamental step toward efficient waste management (UNEP, 2018; Volsuuri et al., 2022)). At the same time, city authorities used water from the sea to intermittently clean drains in the European Towns and some dirty spaces in the Native enclaves. Sanitation inspectors were also trained to inspect houses that did not observe environmental hygiene (Medina-Júnior and Rietzler, 2005; Owusu-Sekyere et al., 2017). By 1929, incinerators were introduced to further treat waste in Ghana. However, shortly after independence, the existing waste management systems broke down. The literature shows that by 1970, the last incinerator was decommissioned, and crude waste dumping into quarry pits began (UN-Habitat, 2010; World Bank, 2021). The beginning of the 1970 s started what has been described by waste managers as the second epoch in waste management planning with the introduction of two refuse collection systems. The first was using wheelbarrows to collect waste from house to house in high-income, low-density, planned communities for monthly fees. The second system reserved specific sites for residents in lower-income, high-density, unplanned communities to dump waste. However, city authorities could not mobilize enough revenue to meet the collection expenditure, which led to a pile-up of waste in many parts of Accra (UNEP, 2018).

The third epoch in Ghana's search efficient solid waste management system was the dawn of the privatization of waste management services. The New Public Management (NPM) approach, already in practice in Europe and the United States, was seen as a timely solution to the social service delivery crises of developing countries, including Ghana. Spearheaded by the Bretton Woods Institutions, Ghana's Structural Adjustment Programme (SAP) was implemented in 1983 to promote economic growth through public sector and institutional reforms, resource mobilization and market liberalization. Short- and medium-term policies were implemented during this period, including privatizing waste management services. The involvement of the private sector, though it injected some momentum and pace into the waste management industry, did not meet the citizens' expectations regarding the quality of waste management services (Volsuuri et al., 2022). The problem is how to develop a waste management system in the local context that delivers effective and efficient waste management services to the citizens.

Legal and policy reforms

One of the key ingredients for an efficient solid waste management system is the availability of robust policy and legal frameworks. Among the policy and legal frameworks guiding waste management include the Local Government Act 936, of 201), the Environmental Protection Agency (EPA) Act, 1994 (Act 490), the Pesticides Control and Management Act, 1996 (Act 528), the Environmental Assessment Regulations, 1999 (LI 1652) and the Health Care Waste Management Policy (2020). Other important waste management guidelines and standards are the Guidelines for Landfill Development and Management in Ghana (2002), the Handbook for the Preparation of District Level Waste Management Plans in Ghana (2002), and the Handbook for the Preparation of District Level Environmental Sanitation Strategies and Action Plans (DESSAPs). The National Environmental Sanitation Policy of Ghana (2010) directly aligns private sector involvement in waste management with the principles of polluter pays, cost recovery (value for money), community participation and equity. Based on the policy, Metropolitan, Municipal and District Assemblies (MMDAs) have direct responsibility for solid waste management within their jurisdictions.

The existing policy regime advocates that in the face of dwindling government resources, local government authorities must maintain an internal capacity to provide at least twenty (20) per cent of solid waste services directly and eighty (80) percent to the private sector. As enshrined in the Ghana National PPP Policy Framework, the success of Private Sector Participation (PSP) depends on an appropriate institutional and regulatory environment and an appropriate risk sharing between the public and private sectors (MoFEP, 2011). According to the World Bank (2021), without strong institutions, regulations and oversight, it isn't easy to achieve the full efficiency and cost-effectiveness that private sector involvement brings. Given the increasing share of plastics in the solid waste stream, a new plastic waste disposal policy was developed in 2018 to address growing concerns about environmental pollution from plastic waste (Vosuuri et al., 2023). The policy comprises seventeen (17) strategic actions. It is based on five focus areas: behaviour change, strategic planning and cross-sectoral collaboration, innovation and transition to the circular economy, resource mobilization, and good governance and shared accountability (Vosuuri et al., 2022). The Ministry of Sanitation and Water Resources (MSWR) was established in 2017 to facilitate private investment and service delivery in the water and sanitation sector (MSWR, 2020; Appiah-Effah et al., 2019). The creation of the new Ministry seems to yield results since it has partnered with the private sector to commence the construction of 16 waste recovery plants in the regional capitals.

Owusu-Sekyere et al. (2015) found that solid waste management policies in Ghana are inadequate and, in some cases, outdated and duplicated. With changing urbanization trends, characteristics and amounts of solid waste, the guidelines must be constantly updated to make them relevant and effective. Policy misalignment and poor coordination are major challenges. Some policies that are supposed to reinforce each other are implemented by different Ministries and Departments with little coordination. While practised by several organizations, the circular economy concept is relatively unknown (Kabera, et al., 2019). As a result, there is no applicable policy for the targeted promotion of the circular economy in Ghana. The drafted plastic waste management policy aimed at promoting a circular economy in the plastic industry in Ghana is yet to be fully implemented.

Methodology

Study area

The study was conducted in four urban communities in the savannah ecological zone of Ghana, illustrated in Fig. 1. The four research locations are Tamale, Sagnarigu, Wa and Bolgatanga. These locations were specifically chosen because of their high population, urbanization and economic activities resulting in high waste generation. The four locations have a combined population of about 729,609, representing 13% of the entire population of Northern Ghana (GSS, 2021). The combined urban population in these centres is 83.4% urbanized compared to the national average of 56.7%. This trend shows great future population increases and possibly serious problems in solid waste management in these cities.

Data collection tools and techniques

Secondary data for three operational years (2018, 2019, and 2020) obtained from waste management companies operating in the selected cities were used for the study. In addition, operation managers of waste companies and officials of the waste management departments were purposively selected and interviewed to validate the secondary data. Data availability and applicability rules were applied in selecting input and output data for the analysis. With relative efficiencies as model outputs, the following were set as input data; the value of total assets, the number of trucks, collection containers, clients, and personnel deployed. The quantity of waste hauled and the amount of revenue generated were the output factors for the four (4) DMUs (Waste companies) operational in Wa, Bolgatanga, Tamale, and Sagnarigu. Using Microsoft Excel Solver, the input-oriented CCR model under Constant Returns to Scale (CRS) was applied for DEA analysis of relative efficiencies. This model was chosen because the DMUs did not operate in perfect competition, and there was more input control.

Efficiency Model

$$Efficiency = \frac{v_1 y_{1o} + v_2 y_{2o} + \cdots + v_r y_{ro}}{u_1 x_{1o} + u_2 x_{2o} + \cdots + u_i x_{io}} \tag{1}$$

u_i *and* v_r are the optimal input weights and the optimal output weights, respectively. x_{io}Inputs of the i variables used and y_{ro} is the output of the r variables used.

2018 Operational Year:

The DEA CCR model for a given DMU was formulated as follows:

$$\text{Target DMU (Max [03B8])} = v_1 y_{1o} + v_2 y_{2o} + \cdots + v_r y_{ro} \tag{2}$$

$$\text{s.t. } u_1 x_{1o} + u_2 x_{2o} + \cdots + u_m x_{mo} = 1 \tag{3}$$

$$v_1 y_{1i} + v_2 y_{2i} + \cdots + v_r y_{ri} \le u_1 x_{1i} + u_2 x_{2i} + \cdots + u_m x_{mi}\ ,\ i = 1, \cdots, n \tag{4}$$

$$u_1, u_2, \cdots, u_m \ \ge 0 \tag{5}$$

$$v_1, v_2, \cdots, u_r \ \ge 0 \tag{6}$$

y_{ro} = amount of output r.
v_r = weight assigned to output r.
x_{io} = amount of input i.
u_i = weight assigned to input i.

The linear programming (LP) formulated out of Table 1 is as follows:

Max: DMU1 (Tamale) = $37699\ v_1 + 23354 v_2$;
Subject to: $2034\ u_1 + 4u_2 + 3645u_3 + 3561u_4 + 51u_5 = 1$;

$$37699v_1 + 23354v_2 - (2034u_1 + 4u_2 + 3645u_3 + 3561u_4 + 51u_5) \le 0$$

$$23270v_1 + 1525v_2 - (2472u_1 + 4u_2 + 2790u_3 + 1073u_4 + 76u_5) \le 0$$

$$25885v_1 + 839v_2 - (1379u_1 + 3u_2 + 3494u_3 + 1088u_4 + 71u_5) \le 0$$

$$3444v_1 + 208v_2 - (43u_1 + 2u_2 + 1934u_3 + 1847u_4 + 55u_5) \le 0$$

$$v_1,\ v_2, u_1, u_2, u_3, u_4, u_5 \ge 0$$

Max: DMU2 (Wa) $= 23270v_1 + 1525v_2$;
Subject to: $2472u_1 + 4u_2 + 2790u_3 + 1073u_4 + 76u_5 = 1$;
$37699\ v_1 + 23354v_2 - (2034u_1 + 4u_2 + 3645u_3 + 3561u_4 + 51u_5) \le 0$;

$$23270v_1 + 1525v_2 - (2472u_1 + 4u_2 + 2790u_3 + 1073u_4 + 76u_5) \le 0$$

$$25885v_1 + 839v_2 - (1379u_1 + 3u_2 + 3494u_3 + 1088u_4 + 71u_5) \le 0$$

$$3444v_1 + 208v_2 - (43u_1 + 2u_2 + 1934u_3 + 1847u_4 + 55u_5) \le 0$$

$$v_1,\ v_2, u_1, u_2, u_3, u_4, u_5 \ge 0$$

Max: DMU3 (Bolgatanga) $= 25885v_1 + 839v_2$;
Subject to:$1379u_1 + 3u_2 + 3494u_3 + 1088u_4 + 71u_5 = 1$;
$37699\ v_1 + 23354v_2 - (2034u_1 + 4u_2 + 3645u_3 + 3561u_4 + 51u_5) \le 0$;

$$23270v_1 + 1525v_2 - (2472u_1 + 4u_2 + 2790u_3 + 1073u_4 + 76u_5) \le 0$$

$25885v_1 + 839v_2 - (1379u_1 + 3u_2 + 3494u_3 + 1088u_4 + 71u_5) \le 0$;
$3444v_1 + 208v_2 - (43u_1 + 2u_2 + 1934u_3 + 1847u_4 + 55u_5) \le 0$;

$$v_1, v_2, u_1, u_2, u_3, u_4, u_5 \ge 0$$

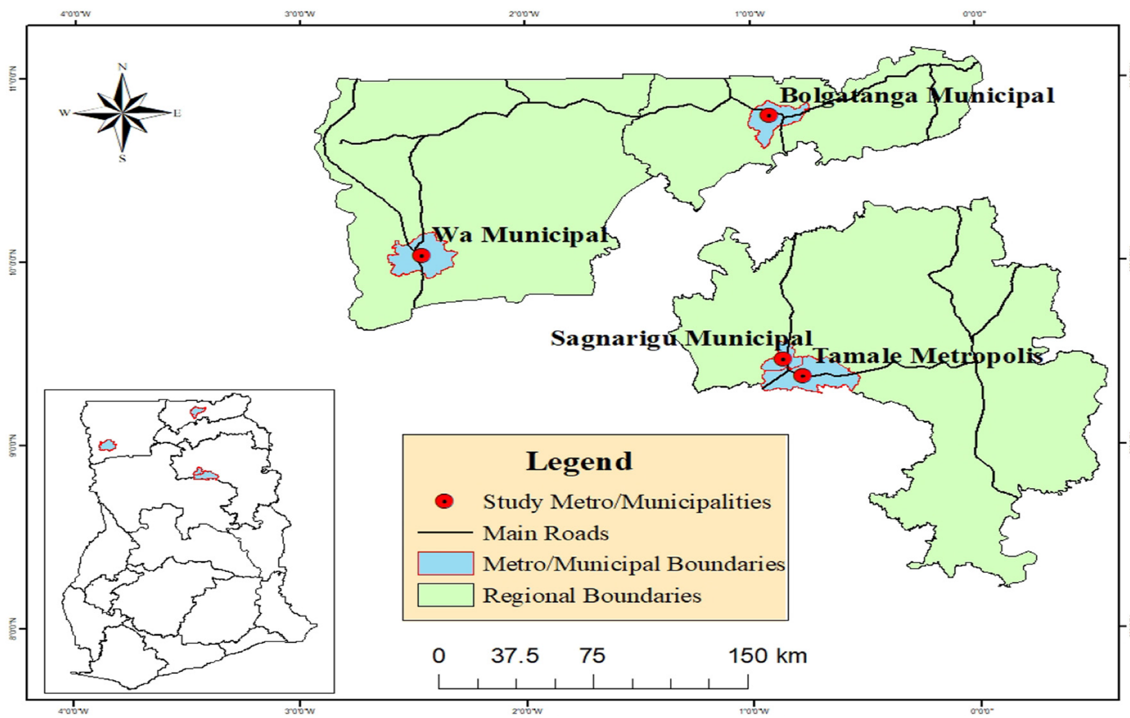

Fig. 1. Maps of study Metropolis and Municipalities.

Table 1
Input and output data for the 2018 operational year.

DMU	x_{1o}	x_{2o}	x_{3o}	x_{4o}	x_{5o}	y_{1o}	y_{2o}
TAMALE	2034	4	3645	3561	51	37,699	2335
WA	2472	4	2790	1073	76	23,270	1,525
BOLGATANGA	1379	3	3494	1088	71	25,885	839
SAGNARIGU	43	2	1934	1847	55	13,444	208

Max: DMU4 (Sagnarigu) $= 3444v_1 + 208v_2$;
Subject to: $1379u_1 + 3u_2 + 3494u_3 + 1088u_4 + 71u_5 = 1$;
$37699\ v_1 + 23354v_2 - (2034u_1 + 4u_2 + 3645u_3 + 3561u_4 + 51u_5) \le 0$;

$23270v_1 + 1525v_2 - (2472u_1 + 4u_2 + 2790u_3 + 1073u_4 + 76u_5) \le 0$

$25885v_1 + 839v_2 - (1379u_1 + 3u_2 + 3494u_3 + 1088u_4 + 71u_5) \le 0$;
$3444v_1 + 208v_2 - (43u_1 + 2u_2 + 1934u_3 + 1847u_4 + 55u_5) \le 0$;

$v_1, v_2, u_1, u_2, u_3, u_{4,} u_5 \ge 0$

2019 Operational Year:

The DEA CCR model for a given DMU in 2019 was formulated as follows:

$$\text{Target DMU (Max [03B8])} = v_1 y_{1o} + v_2 y_{2o} + \cdots + v_r y_{ro} \tag{2}$$

$$u_1 x_{1o} + u_2 x_{2o} + \cdots + u_m x_{mo} = 1 \tag{3}$$

$$v_1 y_{1i} + v_2 y_{2i} + \cdots + v_r y_{ri} \le u_1 x_{1i} + u_2 x_{2i} + \cdots + u_m x_{mi}\ ,\ \ i = 1, \cdots, n \tag{4}$$

$$u_1, u_2, \cdots, u_m \ \ \ge 0 \tag{5}$$

$$v_1, v_2, \cdots, u_r \ \ \ge 0 \tag{6}$$

y_{ro} = amount of output r.
v_r = weight assigned to output r.
x_{io} = amount of input i.
u_i = weight assigned to input i.

The linear programming formulated out of Table 2:

Max: DMU1 (Tamale) $= 51045\ v_1 + 3922v_2$;
Subject to: $1358\ u_1 + 9u_2 + 5962 + 5789u_4 + 79u_5 = 1$;
$51045\ v_1 + 3922v_2 - (1358u_1 + 9u_2 + 5962 + 5789u_4 + 79u_5) \le 0$;

$26870_1 + 1459v_2 - (1864u_1 + 5u_2 + 3165u_3 + 1413u_4 + 76u_5) \le 0$

$26640v_1 + 846v_2 - (1245u_1 + 3u_2 + 3525u_3 + 1313u_4 + 71u_5) \le 0$;
$13208v_1 + 1289v_2 - (298u_1 + 3u_2 + 1893u_3 + 1751u_4 + 55u_5) \le 0$;

$v_1, v_2, u_1, u_2, u_3, u_{4,} u_5 \ge 0$

Max: DMU2 (Wa) $= 26870_1 + 1459v_2$;
Subject to: $1864u_1 + 5u_2 + 3165u_3 + 1413u_4 + 76u_5 = 1$;
$51045\ v_1 + 3922v_2 - (1358u_1 + 9u_2 + 5962 + 5789u_4 + 79u_5) \le 0$;

$26870_1 + 1459v_2 - (1864u_1 + 5u_2 + 3165u_3 + 1413u_4 + 76u_5) \le 0$

$26640v_1 + 846v_2 - (1245u_1 + 3u_2 + 3525u_3 + 1313u_4 + 71u_5) \le 0$;
$13208v_1 + 1289v_2 - (298u_1 + 3u_2 + 1893u_3 + 1751u_4 + 55u_5) \le 0$;

$v_1, v_2, u_1, u_2, u_3, u_{4,} u_5 \ge 0$

Max: DMU3 (Bolgatanga) $= 26640v_1 + 846v_2$;
Subject to: $1245u_1 + 3u_2 + 3525u_3 + 1313u_4 + 71u_5 = 1$;
$51045\ v_1 + 3922v_2 - (1358u_1 + 9u_2 + 5962 + 5789u_4 + 79u_5) \le 0$;

$26870_1 + 1459v_2 - (1864u_1 + 5u_2 + 3165u_3 + 1413u_4 + 76u_5) \le 0$

$26640v_1 + 846v_2 - (1245u_1 + 3u_2 + 3525u_3 + 1313u_4 + 71u_5) \le 0$;

Table 2
Input and output data for the 2019 operational year.

DMU	x_{1o}	x_{2o}	x_{3o}	x_{4o}	x_{5o}	y_{1o}	y_{2o}
TAMALE	1358	9	5962	5789	79	51,045	3922
WA	1864	5	3165	1413	76	26,870	1459
BOLGATANGA	1245	3	3525	1313	71	26,640	846
SAGNARIGU	298	3	1893	1751	55	13,208	1289

$13208v_1 + 1289v_2 - (298u_1 + 3u_2 + 1893u_3 + 1751u_4 + 55u_5) \le 0;$

$v_1, v_2, u_1, u_2, u_3, u_4, u_5 \ge 0$

Max: DMU4 (Sagnarigu) $= 13208v_1 + 1289v_2;$
Subject to:$298u_1 + 3u_2 + 1893u_3 + 1751u_4 + 55u_5 = 1;$
$51045\ v_1 + 3922v_2 - (1358u_1 + 9u_2 + 5962 + 5789u_4 + 79u_5) \le 0;$

$26870_1 + 1459v_2 - (1864u_1 + 5u_2 + 3165u_3 + 1413u_4 + 76u_5) \le 0$

$26640v_1\ + 846v_2 - (1245u_1 + 3u_2 + 3525u_3 + 1313u_4 + 71u_5) \le 0;$
$13208v_1 + 1289v_2 - (298u_1 + 3u_2 + 1893u_3 + 1751u_4 + 55u_5) \le 0;$

$v_1, v_2, u_1, u_2, u_3, u_4, u_5 \ge 0$

2020 Operational Year:

The DEA model for a given DMU system in 2020 was formulated as follows:

$$\text{Target DMU (Max [03B8])} = v_1y_{1o} + v_2y_{2o} + \cdots + v_ry_{ro} \quad (2)$$

$$u_1x_{1o} + u_2x_{2o} + \cdots + u_mx_{mo} = 1 \quad (3)$$

$$v_1y_{1i} + v_2y_{2i} + \cdots + v_ry_{ri} \le u_1x_{1i} + u_2x_{2i} + \cdots + u_mx_{mi}\ ,\ i = 1, \cdots, n \quad (4)$$

$$u_1, u_2, \cdots, u_m \ \ \ge 0 \quad (5)$$

$$v_1, v_2, \cdots, u_r \ \ \ge 0 \quad (6)$$

y_{ro} = amount of output r.
v_r = weight assigned to output r.
x_{io} = amount of input i.
u_i = weight assigned to input i.
The Linear Programming (LP) formulated out of Table 3:
Max: DMU1 (Tamale) $= 57059\ v_1 + 5169v_2;$
Subject to: $685\ u_1 + 9u_2 + 7006 + 6981u_4 + 77u_5 = 1;$
$57059\ v_1 + 5169v_2 - (685u_1 + 9u_2 + 7006 + 6981u_4 + 77u_5) \le 0;$

$30372v_1 + 1931v_2 - (2499u_1 + 6u_2 + 3773u_3 + 1289u_4 + 76u_5) \le 0$

$29301v_1\ + 957v_2 - (965u_1 + 3u_2 + 4029u_3 + 1638u_4 + 71u_5) \le 0;$
$25799v_1 + 5681v_2 - (648u_1 + 3u_2 + 4029u_3 + 2931u_4 + 55u_5) \le 0;$

$v_1, v_2, u_1, u_2, u_3, u_4, u_5 \ge 0$

Max: DMU2 (Wa) $= 30372v_1 + 1931v_2;$
Subject to:$2499u_1 + 6u_2 + 3773u_3 + 1289u_4 + 76u_5 = 1;$
$57059\ v_1 + 5169v_2 - (685u_1 + 9u_2 + 7006 + 6981u_4 + 77u_5) \le 0;$

$30372v_1 + 1931v_2 - (2499u_1 + 6u_2 + 3773u_3 + 1289u_4 + 76u_5) \le 0$

$29301v_1\ + 957v_2 - (965u_1 + 3u_2 + 4029u_3 + 1638u_4 + 71u_5) \le 0;$
$25799v_1 + 5681v_2 - (648u_1 + 3u_2 + 4029u_3 + 2931u_4 + 55u_5) \le 0;$

$v_1, v_2, u_1, u_2, u_3, u_4, u_5 \ge 0$

Max: DMU3 (Bolgatanga) $= 29301v_1 + 957v_2;$
Subject to:$965u_1 + 3u_2 + 4029u_3 + 1638u_4 + 71u_5 = 1;$
$57059\ v_1 + 5169v_2 - (685u_1 + 9u_2 + 7006 + 6981u_4 + 77u_5) \le 0;$

$30372v_1 + 1931v_2 - (2499u_1 + 6u_2 + 3773u_3 + 1289u_4 + 76u_5) \le 0$

$29301v_1\ + 957v_2 - (965u_1 + 3u_2 + 4029u_3 + 1638u_4 + 71u_5) \le 0;$
$25799v_1 + 5681v_2 - (648u_1 + 3u_2 + 4029u_3 + 2931u_4 + 55u_5) \le 0;$

$v_1, v_2, u_1, u_2, u_3, u_4, u_5 \ge 0$

Max: DMU4 (Sagnarigu) $= 25799v_1 + 5681v_2;$
Subject to:$648u_1 + 3u_2 + 4029u_3 + 2931u_4 + 55u_5 = 1;$
$57059\ v_1 + 5169v_2 - (685u_1 + 9u_2 + 7006 + 6981u_4 + 77u_5) \le 0;$

$30372v_1 + 1931v_2 - (2499u_1 + 6u_2 + 3773u_3 + 1289u_4 + 76u_5) \le 0$

$29301v_1\ + 957v_2 - (965u_1 + 3u_2 + 4029u_3 + 1638u_4 + 71u_5) \le 0;$
$25799v_1 + 5681v_2 - (648u_1 + 3u_2 + 4029u_3 + 2931u_4 + 55u_5) \le 0;$

$v_1, v_2, u_1, u_2, u_3, u_4, u_5 \ge 0$

Results and discussion

The results and discussions are presented based on the operational years. The purpose is to isolate the factors that accounted for the efficiencies of the DMUs in each study area. The results for each operational year are presented on the assumption that:
All data and weights are positive,
Efficiency scores lie between zero and one,
The same weights for the target city are applied to all cities.

Efficiency scores for the 2018 operational year

The results obtained from the DEA using the CCR model for the year 2018 operational year show that the DMUs in three cities (Bolgatanga, Sagnarigu and Wa) were efficient and were considered to have performed better. This is evidenced by their efficiency score, which equals one (1.00) on the efficient frontier (Table 4). In short, the DMUs in the three cities were more efficient in converting inputs into better waste management performance than Tamale (0.000519), which was inefficient.

The optimal solution to linear programming (LP) has the value of one (1), and the best input and output weights were $u_1 = 7.12322E - 05, u_2 = 0.0,\ \ u_3 = 0.000253798,\ \ u_4 = 1.37878E-05,\ u_5 = 0,\ v_1 = 3.86324E - 05$, and $v_2 = 0$ (Table 5). The following findings were made after observing the differences between the opti-

Table 3
Input and output data for the 2020 operational year.

DMU	x_{1o}	x_{2o}	x_{3o}	x_{4o}	x_{5o}	y_{1o}	y_{2o}
TAMALE	685	9	7006	6981	77	57,059	5169
WA	2499	6	3773	1289	76	30,372	1931
BOLGATANGA	965	3	4039	1638	71	29,301	957
SAGNARIGU	648	3	4029	2931	55	25,799	5681

mal weights: the ratio between the number of dustbins serviced and total assets ($\frac{u_3}{u_1}$)was 3.56, suggesting that it will be advantageous for Tamale to weigh the input of the number of dustbins serviced by 3.56 times more than the input of total assets to maximize efficiency. In other words, a reduction in the input number of dustbins serviced has a bigger effect on efficiency than makes a reduction in total assets as input (see Table 6).

Again, the ratio between the number of clients serviced and total assets ($\frac{u_4}{u_1}$)was 5.17, suggesting that it will be advantageous for Tamale to weigh the input of the number of clients serviced by 5.17 times more than the input of total assets to maximize efficiency. In other words, a reduction in the input number of clients serviced has a bigger effect on efficiency than makes a reduction in total assets as input. It is also worth noting that the ratio between the number of dustbins serviced and the number of clients serviced ($\frac{u_3}{u_4}$)was 18.41, which means that it will be advantageous for Tamale to weigh the input of the number of dustbins serviced by 18.41 times more than the input of the number of clients serviced to maximize efficiency. This means that reducing the input number of dustbins serviced has a bigger effect on efficiency than reducing the number of clients serviced as input. Generally, to maximize efficiency, the number of clients serviced, dustbins serviced, and total assets should not increase for the same output. Bakobie et al. (2018) observed that cost-effective municipal waste collection could be achieved by focusing on fuel consumption, distance travelled, and truck maintenance costs. The number of trucks and staff has a neutral effect on maximizing efficiency to get the same output for 2018. These findings differed from the conclusion of Bakobie et al. (2018) that operating cost, including labour cost, is key to improving the efficiency of waste collection.

To improve efficiency, the input target, which is the actual input for the inefficient city, should be multiplied by the relative efficiency for the inefficient city. So, for Tamale to have efficiency in service delivery, the input target = (2034 total assets + 4 number of trucks deployed + 3645 number of dustbins serviced + 3561 number of clients serviced + 51 number of staff) × 0.000519 = 1.1 total assets + 2.1E^{-3} number of trucks deployed + 2 number of dustbins serviced + 2 number of clients serviced + 2.6E$^{\mathord{-}\ 2}$ number of staff. Tamale will be efficient if it reduces its number of dustbins and clients serviced to 2 and 2, respectively, with virtually zero for the rest of the inputs to yield the same output. Table 3 also indicated that the three working constraints (Bolgatanga, Sagnarigu and Wa) with a slack value of zero were said to be binding because they were satisfied with equality at the LP optimal.

From Table 7, the best input and output weights for $u_1 = 7.12322E-05, u_2 = 0.0,\ \ u_3 = 0.000253798,\ \ u_4 = 1.37878E-05$, $u_5 = 0$, $v_1 = 3.86324E-05$, and $v_2 = 0$. Assuming the coefficient of v_1 is varied in the objective function, the solution value for v_1 will be $3.86324E-05$ and the objective function coefficient for v_1 will be 25885. The allowable increase or decrease indicates that provided the coefficient for v_1 in the objective function lies between 25885 + 1E + 30 = 25886 and 25885–0 = 25885, the values of the variables in the optimal LP solution will remain unchanged. Again, the solution value for u_3 was 0.000253798, and the objective function coefficient for u_3 was 0, the allowable increase or decrease tells us that, provided the coefficient for u_3 in the objective function lies between 0 + 2251.761624 = 2251.761624 and 0–0 = 0, the values of the variables in the optimal LP solution will remain unchanged. Similar conclusions may be drawn for u_2, u_4, u_5, and v_1.

Table 8 shows the varying effect of the right-hand side of the Wa constraint can be observed. Since the right-hand side of the Wa constraint lies between 0 + 0.035479006 = 0.035479006 and 0—0.65738932 = -0.65738932, the objective function change will be exactly zero (0). Again, since the right-hand side of the Bolgatanga constraint lies between 0 + 0.571492264 = 0.57149224 and 0–0.018797555 = -0.018797555, the objective function change will be exactly zero (0).

Table 4
Efficiency Scores of the Cities.

City	Efficiency
Tamale	5.19*10^{-4}
Wa	1.00
Bolgatanga	1.00
Sagnarigu	1.00

Table 5
Optimal weights for Bolgatanga as the target DMU.

Name	Original value	Final value
Weight (v_1) Quantity of waste hauled (tons)	1.0000	3.86324E-05
Weight (v_2) Revenue generated'000 (GHS)	1.0000	0
Weight (u_1) Total assets (000) GHS	1.0000	7.12322E-05
Weight (u_2) Number of trucks deployed	1.0000	0
Weight (u_3) Number of dustbins serviced	1.0000	0.000253798
Weight (u_4) Number of clients serviced	1.0000	1.37878E-05
Weight (u_5) Number of staff	1	0

Table 6
Constraints of the Model for Bolgatanga as the Target DMU.

City	Cell value	Status	Slack
BOLGATANGA (Weighted input)	1	Binding	0
TAMALE (Working)	−2804.66268	Not Binding	2804.66268
WA (Working)	0	Binding	0
BOLGATANGA (Working)	0	Binding	0
SAGNARIGU (Working)	0	Binding	0

Table 7
Sensitivity report on the optimal weights for Bolgatanga as the target DMU.

Name	Final value	Reduced cost	Objective coefficient	Allowable increase	Allowable decrease
Weight (v_1) Quantity of waste hauled (tons)	3.86324E-05	0	25,885	1E + 30	0
Weight (v_2) Revenue generated'000 (GHS)	0	0	839	0	1E + 30
Weight (v_1) Total assets (000) GHS	7.12322E-05	0	0	0	0
Weight (u_2) No. of trucks deployed	0	0	0	0	1E + 30
Weight (u_3) Number of dustbins serviced	0.000253798	0	0	2251.761624	0
Weight (u_4) Number of clients serviced	1.37878E-05	0	0	0	0
Weight (u_5) Number of staff	0	0	0	0	1E + 30

Table 8
Sensitivity Report on the Constraints of the Model for Bolgatanga as Target DMU.

City	Final value	Shadow price	Constraint RH side	Allowable increase	Allowable decrease
BOLGATANGA Weighted input	1	1	1	8314.411091	1
TAMALE Working	−2804.662675	0	0	1E + 30	2804.662675
WA Working	0	0	0	0.035479006	0.65738932
BOLGATANGA Working	0	1	0	0.571492264	0.018797555
SAGNARIGU Working	0	2.22045E-16	0	0.018642189	0.646503735

Table 9
Efficiency Scores of the Cities.

City	Efficiency
Tamale	1.00
Wa	1.00
Bolgatanga	1.00
Sagnarigu	0.81

Table 10
Optimal weights for Bolgatanga as the target DMU.

Name	Original value	Final value
Weight (v_1) Quantity of waste hauled (tons)	1	3.75375E-05
Weight (v_2) Revenue generated'000 (GHS)	1	0
Weight (u_1) Total assets (000) GHS	1	0
Weight (u_2) No. of trucks deployed	1	0.046864131
Weight (u_3) Number of dustbins serviced	1	0.000239548
Weight (u_4) Number of clients serviced	1	1.14256E-05
Weight (u_5) Number of staff	1	0

Table 11
Constraints of the Model for Bolgatanga as the Target DMU.

City	Cell value	Status	Slack
BOLGATANGA Weighted input	1	Binding	0
TAMALE Working	0	Binding	0
WA Working	0	Binding	0
BOLGATANGA Working	0	Binding	0
SAGNARIGU Working	−0.1182667	Not Binding	0.1182667

Efficiency scores for the 2019 operational year

In 2019, three cities (Bolgatanga, Tamale and Wa) were efficient and were considered to have better efficiency performances (Table 9). These efficient cities had efficiency scores equal to one (1.00) on the efficient frontier. The three cities were more efficient in converting inputs into better waste management performance than Sagnarigu (0.81), which was inefficient. Sagnarigu's efficiency might be determined by comparing it to any of the three efficient cities. Table 9 shows the efficiency scores of the four cities obtained from DEA using the CCR model.

In Table 10, the optimal solution to linear programming (LP) has the value of one (1), and the best input and output weights were $u_1 = 0, u_2 = 0.046864131$, $u_3 = 0.000239548$, $u_4 = 1.14256E - 05$, $u_5 = 0$, $v_1 = 3.75375E - 05$, and $v_2 = 0$. The following findings were made after observing the differences between the optimal weights. The ratio between the number of trucks deployed and the number of dustbins serviced ($\frac{u_2}{u_3}$)was 195.64, suggesting that it was advantageous for Sagnarigu to weigh the input of the number of trucks deployed by 195.64 times more than the input of the number of dustbins serviced to maximize its efficiency. In other words, reducing the input number of trucks deployed has a bigger effect on efficiency than reducing the number of dustbins serviced as input. Again, the ratio between the number of trucks deployed and the number of clients serviced ($\frac{u_2}{u_4}$)was 4101.68, indicating that it was advantageous for Sagnarigu to weigh the input of the number of trucks deployed 4101.68 times more than the input of the number of clients serviced to maximize its efficiency. Reducing the input number of trucks deployed has a bigger effect on efficiency than reducing the number of clients serviced as input. It is also worth noting that the ratio between the number of dustbins serviced and the number of clients serviced ($\frac{u_3}{u_4}$)was 20.97. This means that it was advantageous for Sagnarigu to weigh the input of the number of dustbins serviced 20.97 times more than the input of the number of clients serviced to maximize its efficiency. Reducing the input number of dustbins serviced has a bigger effect on efficiency than reducing the number of clients serviced as input. Generally, to maximize efficiency, the number of clients serviced, dustbins serviced, and trucks should not increase for the same output. The total assets and the number of staff neutralize maximizing efficiency to get the same output for 2019. From this perspective, if the DMUs in Sagnarigu want to improve their efficiency, then the input target, which is the actual input, should be multiplied by the relative efficiency. That is input target = (298 total assets + 3 number of trucks deployed + 1893 number of dustbins serviced + 1751 number of clients serviced + 55 number of staff) × 0.81 = 241 total assets + 2 number of trucks deployed + 1533 number of dustbins serviced + 1418 number of clients serviced + 45 number of staff. This means that Sagnarigu will be efficient with the same targeted output if it reduces its total assets, the number of trucks deployed, the number of dustbins serviced, the number of clients serviced, and the number of staff to 241, 2, 1533, 1418 and 45 respectively.

Table 11 analyses the three working constraints (Bolgatanga, Tamale and Wa) with a slack value of zero which is argued to be binding because they were satisfied with equality at the LP optimal.

With variation in the coefficient of v_1 in the objective function was varied, the solution value for v_1 was $3.75375E - 05$ and the objective function coefficient for v_1 was 26,640 (see Table 12). The allowable increase or decrease tells us that, provided the coefficient for v_1 in the objective function lies between 26640 + 1E + 30 = 26640 and 25885–0 = 25885, the values of the variables in the optimal LP solution will remain unchanged. Again, the solution value for u_2 was 0.046864131, and the objective function coefficient for u_2 was 0, the allowable increase or decrease tells us that, provided the coefficient for u_2 in the objective function lies between 0 + 0 = 0 and 0–0 = 0, the values of the variables in the optimal LP solution will remain unchanged. Similar conclusions may be drawn for u_3, u_4, u_5, and u_1.

In Table 13, the changing effect of the right-hand side of the Wa constraint was examined. It was observed that since the right-hand side of the Wa constraint lies between 0 + 0.096016304 = 0.096016304 and 0—0.021276208 = -0.021276208, the change in objective function will be exactly zero

Table 12
Sensitivity report on the optimal weights for Bolgatanga as the target DMU.

Name	Final value	Reduced cost	Objective coefficient	Allowable increase	Allowable decrease
Weight (v_1) Quantity of waste hauled (tons)	3.75375E-05	0	26,640	1E + 30	0
Weight (v_2) Revenue generated'000 (GHS)	0	0	846	0	1E + 30
Weight (u_1) Total assets (000) GHS	0	−1.137E-13	0	1.137E-13	1E + 30
Weight (u_2) No. of trucks deployed	0.046864131	0	0	0	0
Weight (u_3) Number of dustbins serviced	0.000239548	0	0	2562.995339	0
Weight (u_4) Number of clients serviced	1.14256E-05	0	0	0	0
Weight (u_5) Number of staff	0	0	0	0	1E + 30

Table 13
Sensitivity Report on the Constraints of the Model for Bolgatanga as Target DMU.

City	Final value	Shadow price	Constraint RH side	Allowable increase	Allowable decrease
BOLGATANGA Weighted input	1	1	1	1E + 30	1
TAMALE Working	0	0	0	0.036216659	1.463564919
WA Working	0	0	0	0.096016304	0.021276208
BOLGATANGA Working	0	1	0	0.613959754	0.108747505
SAGNARIGU Working	0.118266695	0	0	1E + 30	0.118266695

Table 14
Efficiency Scores of the Cities.

City	Efficiency
Tamale	1.00
Wa	1.00
Bolgatanga	1.00
Sagnarigu	0.86

Table 15
Optimal weights for Bolgatanga as the target DMU.

Name	Original value	Final value
Weight (v_1) Quantity of waste hauled (tons)	1	3.41285E-05
Weight (v_2) Revenue generated'000 (GHS)	1	0
Weight (u_1) Total assets (000) GHS	1	0
Weight (u_2) No trucks deployed	1	0.033580563
Weight (u_3) Number of dustbins serviced	1	0.00021429
Weight (u_4) Number of clients serviced	1	2.05984E-05
Weight (u_5) Number of staff	1	0

(0). Again, since the right-hand side of the Bolgatanga constraint lies between 0 + 0.613959754 = 0.613959754 and 0–0.108747505 = -0.108747505, the objective function change will be exactly zero (0).

Efficiency scores for the 2020 operational year

The results also show that for 2020, the DMUs in Bolgatanga, Tamale and Wa operated efficiently. The cities had efficiency scores equal to one (1.00) on the efficient frontier. The three cities were more efficient in converting inputs into better waste management performance than Sagnarigu (0.81), which was inefficient. The efficiency scores of the four cities obtained from DEA using the CCR model are shown in Table 14.

In Table 15, the optimal solution to linear programming (LP) has the value of one (1), and the best input and output weights were $u_1 = 0, u_2 = 0.033580563$, $u_3 = 0.00021429$, $u_4 = 2.05984E-05$, $u_5 = 0$, $v_1 = 3.41285E-05$, and $v_2 = 0$. The following findings were made after observing the differences between the optimal weights. For instance, the ratio between the number of trucks deployed and the number of dustbins serviced ($\frac{u_2}{u_3}$)was156.71. This suggests that it was advantageous for Sagnarigu to weigh the input of the number of trucks deployed 156.71 times more than the input of the number of dustbins serviced to maximize efficiency. Reducing the input number of trucks deployed has a bigger effect on efficiency than reducing the number of dustbins serviced as input. Again, the ratio between the number of trucks deployed and the number of clients serviced ($\frac{u_2}{u_4}$)was 1630.25, suggesting that it was advantageous for Sagnarigu to weigh the input of the number of trucks deployed 1630.25 times more than the input of the number of clients serviced to maximize its efficiency. In other words, reducing the input number of trucks deployed has a bigger effect on efficiency than reducing the number of clients serviced as input. It is also worth noting that the ratio between the number of dustbins serviced and the number of clients serviced ($\frac{u_3}{u_4}$)was 10.40. This means that it was advantageous for Sagnarigu to weigh the input of the dustbins serviced 10.40 times more than the input of the number of clients serviced to maximize its efficiency. In other words, reducing the input number of dustbins serviced has a bigger effect on efficiency than reducing the number of clients serviced as input. Generally, to maximize efficiency, the number of clients serviced, dustbins serviced, and trucks should not increase for the same output. The total assets and the number of staff neutralize maximizing efficiency to get the same output for 2020.

Table 16
Constraints of the Model for Bolgatanga as the Target DMU.

City	Cell value	Status	Slack
BOLGATANGA (Weighted input)	1	Binding	0
TAMALE (Working)	0	Binding	0
WA (Working)	0	Binding	0
BOLGATANGA (Working)	0	Binding	0
SAGNARIGU (Working)	0.14400894	Not Binding	0.14400894

Table 17
Sensitivity report on the optimal weights for Bolgatanga as the target DMU.

Name	Final value	Reduced cost	Objective coefficient	Allowable increase	Allowable decrease
Weight (v_1) Quantity of waste hauled (tons)	3.41285E-05	0	29,301	1E + 30	6.96163E-12
Weight (v_2) Revenue generated'000 (GHS)	0	−2.27374E-13	957	2.27374E-13	1E + 30
Weight (u_1) Total assets (000) GHS	0	0	0	0	1E + 30
Weight (u_2) No. of trucks deployed	0.033580563	0	0	3.79551E-16	0
Weight (u_3) Number of dustbins serviced	0.00021429	0	0	3169.37085	0
Weight (u_4) Number of clients serviced	2.05984E-05	0	0	0	4.13895E-13
Weight (u_5) Number of staff	0	0	0	0	1E + 30

Table 18
Sensitivity Report on the Constraints of the Model for Bolgatanga as Target DMU.

City	Final value	Shadow price	Constraint RH side	Allowable increase	Allowable decrease
BOLGATANGA Weighted input	1	1	1	1E + 30	1
TAMALE Working	0	1.38778E-17	0	0.091168833	2.054898735
WA Working	0	1.11022E-16	0	0.114801548	0.076791592
BOLGATANGA Working	0	1	0	0.215599503	0.099829433
SAGNARIGU Working	0.14400894	0	0	1E + 30	0.14400894

To improve the efficiency of Sagnarigu, the input target, which is the actual input for Sagnarigu, should be multiplied by the relative efficiency for Sagnarigu. For Sagnarigu to have efficiency,

input target = (648 total assets + 3 number of trucks deployed + 4029 number of dustbins serviced + 2931 number of clients serviced + 55 number of staff) × 0.86 = 557 total assets + 3 number of trucks deployed + 3465 number of dustbins serviced + 2521 number of clients serviced + 47 number of staff. This means that Sagnarigu will be efficient with the same targeted output if it reduces its total assets, the number of trucks deployed, the number of dustbins serviced, the number of clients serviced, and the number of staff to 557, 3, 3465, 2521 and 47 respectively.

Table 16 indicates that the three working constraints (Bolgatanga, Tamale and Wa) with a slack value of zero were said to be binding because they were satisfied with equality at the LP optimal.

From Table 17, the optimal input and output weights were $u_1 = 0, u_2 = 0.033580563$, $u_3 = 0.00021429$, $u_4 = 2.05984E - 05$, $u_5 = 0$, $v_1 = 3.41285E - 05$, and $v_2 = 0$. Suppose we varied the coefficient of v_1 in the objective function, the solution value for v_1 was $3.41285E - 05$ and the objective function coefficient for v_1 was 29301. The allowable increase or decrease tells us that, provided the coefficient for v_1 in the objective function lies between 29301 + 1E + 30 = 29301 and 29301–6.96163E-12 = 29301, the values of the variables in the optimal LP solution will remain unchanged. Again, the solution value for u_3 was 0.00021429, and the objective function coefficient for u_3 was 0, the allowable increase or decrease tells us that, provided the coefficient for u_3 in the objective function lies between 0 + 3169. 37085 = 3169.37085 and 0–0 = 0, the values of the variables in the optimal LP solution will remain unchanged. Similar conclusions may be drawn for u_2, u_4, u_5, and v_1.

From Table 18, the changing effect of the right-hand side of the Wa constraint can be observed. Since the right-hand side of the Wa constraint lies between 0 + 0.114801548 = 0.114801548 and 0—0.076791592 = -0.076791592, the objective function change will be exactly zero (0). Again, since the right-hand side of the Bolgatanga constraint lies between 0 + 0.215599503 = 0.215599503 and 0–0.099829433 = -0.099829433, the objective function change will be exactly zero (0).

Summary of efficiency scores for the three operational years

Over the years, the main argument driving waste management research is whether the private sector's involvement has improved waste collection efficiency (Bernache Pérez, 2006; Couto and Hern, 2012). Studies in Ghana agree that private waste management services are usually more efficient than the public sector (Oteng-Ababio et al., 2017; Alhassan et al., 2020). These studies compared waste collection efficiency between the public and private sectors. In this study, the efficiency assessment was among the private companies that compete to procure service contracts from the public regulator. The summaries of the descriptive statistics of the results are presented in Table 19. The maximum efficiency score was 1.00 for all the operational years, while the minimum was $5.19*10^{-4}$T, 0.81 and 0.97 for 2018, 2019 and 2020, respectively. The efficiency score average for 2018, 2019 and 2020 were 0.75, 0.95 and 0.97, respectively. This implies that the input for an average unit may have to be increased by 25%, 5% and 3% for 2018, 2019 and 2020 to improve efficiency.

The results compare with similar studies conducted in Spanish on the solid waste sector by Bosch et al. in 2000. They reported that the average efficiencies were 0.85 for the DMUs selected for the study. Similarly, Worthington and Dollery (2001) indicated that waste management companies are not operating efficiently in Australia, as their efficiency scores ranged between 0.60 and 0.80 for MSW collection.

Table 19
Descriptive statistics for DEA results.

Item description	Scores		
	2018	2019	2020
Total number of DMUs	4	4	4
Number of efficient DMUs	3	3	3
Number of inefficient DMUs	1	1	1
Maximum efficiency	1	1	1
Minimum efficiency	5.19*10–4	0.81	0.86
Average efficiency	0.75	0.95	0.97

Conclusion

The article has presented insights on the efficiency of solid waste management by private companies in selected urban centres in Ghana based on an in-depth analysis of Ghana's emerging cities experiencing rapid expansion. The article illuminates how waste management companies produce inefficiencies through limited resource inputs. The findings illuminate how the optimal combination of assets, labour, number of trucks and waste collection bins can improve waste collection efficiency. Theoretically, the article presents several suggestions for waste managers and policymakers in Ghana. First, the wholesale thinking that introducing the private sector into service provision is enough to enhance efficiency may have to be revisited. Rather, policymakers should ensure that the private sector has the resource capacity to operate efficiently using the right input–output mix. Second, the enabling environment necessary for the private sector to function efficiently should be created for all key stakeholders. This means that all must set and agree upon the right legal framework and supportive institutional environments that can facilitate the right input–output combination to guide policy implementation.

Availability of data and materials

The dataset used in this paper is available and accessible upon request from the corresponding author.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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