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Environmental Assessment of Wastewater Treatment-based Resource Recovery in Nigeria

DISSERTATION THESIS

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Declaration

I hereby affirm that I have done this thesis entitled **“Environmental Assessment of Wastewater Treatment-based Resource Recovery in Nigeria”** independently, except for jointly authored publications that are included. In the case of such publications, my specific contributions to each chapter have been clearly stated at their respective beginnings. Furthermore, I affirm that proper acknowledgement has been provided within this thesis for any references made to the works of others. I also ensure that this work has not been and is not being submitted for any other degree from this or any other university. All the sources have been quoted and acknowledged by means of complete references and according to the Citation rules of the FTA.

In Prague, September 10th, 2024

Charles Amarachi Ogbu

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Abstract

Wastewater treatment is central to environmental and public health sustainability while inherently offering valuable resources that can be utilized. This thesis provided an overview of the current environmental performance of water and wastewater treatment in Africa, specifically studies adopting the Life Cycle Assessment (LCA) methodology. Secondly, a glimpse of the volume of wastewater generation in Nigeria and the potential energy recovery was furnished. The performance of a wastewater treatment plant (WWTP) was evaluated based on pollutant removal efficiency, effluent quality, and greenhouse gas (GHG) emissions. Thirdly, energy recovery alternatives at the WWTP were further investigated, including assessing economic viability and potential environmental impacts. The adoption of LCA in Africa has progressed, with researchers aiming to understand and advance treatment technologies. Global Warming Potential (GWP) was a key concern, mainly from fossil fuel-derived electricity. Utilizing renewable energy sources, resource recovery, and robust data practices are essential to fostering sustainability. The scarcity of LCA reports on water treatment in Nigeria underscores the need to integrate LCA into local standards, engineering designs, and academic curricula. Performance assessment of WWTPs highlighted high removal rates for organic matter and coliforms, but varying nitrates and coliform content in effluent threaten water bodies. GHG emissions, primarily methane from biological processes, contributed significantly to GWP. Addressing these emissions is crucial for reducing environmental impacts. Wastewater generation of 1.05 x 10^9 m^3/year was estimated in Nigeria, and the energy potential at regional and facility levels was uncovered. According to comparative analyses, Anaerobic Digestion (AD) had a competitive net present value (NPV) and shorter payback periods. Hydroelectric power at treatment facilities offered desirable levelized cost of energy and NPV. Incineration (INC) was cost-effective at a centralized level. Hydroelectric power demonstrated an emission-free operational profile, while AD outperformed INC on the overall environmental assessment. Mitigation measures against exhaust emissions can reduce environmental impacts, and energy recovery can offset environmental footprints. This research offered insights that could instigate investments in energy recovery technologies in the Nigerian water sector. It also provided additional information for policymakers that would impact the Renewable Energy Master Plan and the National Environmental Sanitation Policy.

Keywords: Energy Use; Carbon Footprint; Treatment Efficiency; Economic Feasibility; Energy Self-sufficiency.

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1. Introduction

Globally, large volumes of wastewater are treated daily to prevent adverse effects on humans and the environment (Anyadiegwu & Ohia, 2015). Inadequate management of wastewater in developing nations has resulted in the spread of diseases, a concern directly addressed by Sustainable Development Goal (SDG) 6, which aims to decrease the discharge of untreated wastewater into the environment. Unfortunately, compliance with wastewater discharge standards remains low in many developing countries, with over 80% of sewage being inadequately treated before discharge (UN Water, 2022).

The expansion of populations, economic development, and insufficient water and sanitation infrastructure in low- and lower-middle-income countries, particularly in Africa, have significantly increased exposure to pollution (UNEP, 2016; WWAP, 2017). Wastewater treatment plants (WWTPs) are crucial in pollution control safeguarding public and environmental health. While advancements in wastewater treatment (WWT) have improved public health and local water quality over the years (Heimersson et al., 2014), adhering to stringent discharge standards necessitates using chemicals, resources, and energy. In most developed nations, these facilities predominantly rely on fossil fuel energy, leading to economic and environmental ramifications (Li et al., 2021; UNEP, 2016; WWAP, 2017). The performance of WWTPs is affected by various factors, including population demographics, living standards, economic development (Li et al., 2021), ambient temperature, discharge regulations, electricity tariffs, geographic characteristics, industrial landscape (Cardoso et al., 2021), electricity sources (Wang et al., 2016), technology, scale, policy, and governance (Longo et al., 2016). The impact of effluent on recipients is determined by pollutant concentrations, regional environmental factors (Lehtoranta et al., 2014), weather conditions, increased runoff, and seasonal variations (Lehtoranta et al., 2014; Platikanov et al., 2014).

Energy expenses represent the most significant operational cost for WWTPs in developed and developing countries (Montwedi et al., 2021). Electricity consumption typically accounts for 60-90% of total energy usage in WWTPs, with energy costs comprising 20-40% of operational expenses (Sun et al., 2019). Globally, wastewater treatment consumes approximately 3-5% of total electricity consumption (Power et al., 2014). In South Africa, these systems consume over 50% of energy in the water sector, contributing 25% of urban energy consumption (Montwedi et al., 2021). Similarly, in the United States, the production and distribution of potable water, along with wastewater collection and treatment, contribute to 4% of total electricity demand (Longo et al., 2016). In certain European regions, WWTPs account for 1% of national electricity consumption

(Longo et al., 2016). The annual carbon footprint of WWTPs in Nordic countries ranges from 7-108 kg CO_2eq/pe, primarily influenced by Scope 1 and 2 emissions (Power et al., 2014). Approximately 0.25% of national energy consumption in China is attributed to WWTPs (Sun et al., 2019).

Hygiene facilities play crucial roles in society, industry, and environmental sustainability and are subject to rigorous regulation. Failure to comply with discharge regulations can result in legal repercussions, fines, and economic burdens due to remediation efforts and healthcare expenses. In many developing nations, adherence to discharge regulations is infrequent and entails significant financial and environmental implications (UNEP, 2016; WWAP, 2017). The operations of WWTPs generate greenhouse gases (GHGs), contributing to global warming (Corominas et al., 2013). The deterioration of river water quality, linked to health risks such as high sodium and salinity, threatens communities. Effluent pollutants adversely affect water quality and aquatic ecosystems in rivers and lakes, resulting in eutrophication, algal blooms, habitat degradation, biodiversity loss, and ecosystem imbalances. The agricultural application of sludge and effluent containing heavy metals and micropollutants can lead to ecotoxicity (Corominas et al., 2013). The effluent infiltration into the soil can contaminate it, affecting fertility and agricultural productivity. Emissions from fossil fuel-based energy sources in WWTPs can create acidification and photochemical oxidation (Gallego-Schmid et al., 2019). Therefore, unregulated WWTP activities pose substantial hazards to human health and the environment.

The treatment of wastewater generates substantial quantities of sewage sludge, which offers opportunities for potential resource recovery (water, energy, nutrients, carbon). These valuable resources can be reclaimed through various methods, such as biogas production and sludge utilisation in agricultural practices, or even potentially as raw materials for biopolymers (Heimersson et al., 2014). Motivations behind resource recovery efforts include (i) mitigating eutrophication of water bodies caused by effluent from WWTPs, (ii) reducing reliance on chemical fertilisers, (iii) minimising GHG emissions associated with conventional fertiliser production methods, and (iv) capitalising on the sustainable nature of these materials, as wastewater is continuously generated due to human and industrial activities. Energy can also be reclaimed through biological or thermal/thermo-chemical sewage sludge treatment, resulting in biogas, heat, steam, and electricity (Kleemann et al., 2015; Mayer et al., 2016). However, recent concerns have emerged regarding the broader environmental and economic implications of wastewater and sludge treatment with or without material recovery and the final use or disposal of recovered resources (Egle et al., 2016). The recovery of these materials is expected to entail additional costs in terms of energy, time, labour, water, materials, and environmental emissions. It underscores the necessity to scrutinise and evaluate the processes involved to ascertain their environmental and economic viability.

Life Cycle Assessment (LCA), along with the best available techniques and model development, has been employed to identify emission sources and estimate on-site and off-site emissions at WWTPs (IPCC, 2019; Kyung et al., 2015; Mannina et al., 2016). Numerous studies underscore the significant influence of wastewater source, geographical location, treatment scales, technologies, and configurations on GHG emissions, electricity consumption, and sludge production (Lam et al., 2020; Ogbu et al., 2023; Wu et al., 2022). Additionally, stringent discharge limits can lead to increased GHG emissions, highlighting the importance of considering both environmental impacts and emissions when formulating standards (Zhou et al., 2022). The LCA, per ISO 14040 series (Finkbeiner et al., 2006) consists of four phases. The first phase, known as goal and scope definition, involves outlining the study's objectives, defining the system and its boundaries, and determining the functional unit. During the Life Cycle Inventory (LCI) phase, the material and energy flows within the system are identified and quantified. Subsequently, in the Life Cycle Inventory Assessment (LCIA) phase, these flows are translated into environmental impact indicators, either midpoint or endpoint indicators, based on the selected assessment model. Commonly utilised models in WWTP studies include IPCC, CML, Eco-indicator, and ReCiPe (Diaz-Elsayed et al., 2020). In the interpretation phase, the results obtained from the LCI and LCIA phases are analysed in alignment with the predetermined goals. Additionally, this phase involves conducting data quality checks, comparing findings with existing literature, and discussing the limitations of the study. The LCI and LCIA phases are often facilitated by commercial software packages such as SimaPro, GaBi, and OpenLCA (Morsy et al., 2020). On the other hand, Life Cycle Cost Analysis (LCCA) typically encompasses the expenses associated with the ownership, operation, and maintenance of a facility throughout its life cycle (Valladares Linares et al., 2016). Commonly reported cost analyses for Water and Wastewater Treatment facilities include Uniform Annual Cash Flow (UAC), Net Present Value (NPV) (Diaz-Elsayed et al., 2020), capital costs (CAPEX) (Sikosana et al., 2017), and operational costs (OPEX) (Masindi et al., 2018). Other analyses include cost-benefit analysis, financial rate of return, and the weighted average cost of capital (Pinelli et al., 2020).

1.1 Current situation in Nigeria

Nigeria faces a significant public health challenge concerning inadequate access to safe drinking water and sanitation (FMWR et al., 2022). An estimated 80 million people lack access to secure hygiene facilities, with approximately 29% of rural households resorting to open defecation (World Bank, 2021). This situation results in the discharge of considerable volumes of untreated or inadequately treated wastewater into the environment. Inadequate access to safe drinking water and sanitation in Nigeria exacerbates public health issues (FMWR et al., 2022). Roughly 46% of the population lacks access to basic sanitation, contributing to widespread water pollution (FMWR et al., 2022). Moreover, 11% of households report recent cases of diarrhoea (FMWR et al., 2022). Only a small proportion of the population, around 10%, has access to basic water, sanitation, and hygiene services, while 23% practice open defecation (FMWR et al., 2022). Additionally, comprehensive data on the volume and distribution of wastewater in Nigeria remains elusive. Despite numerous efforts to estimate wastewater generation, collection, and treatment, existing attempts have failed to account for the specificities and variations in sanitation practices, water accessibility per capita, and population growth rates.

Developing countries, including Nigeria, encounter major challenges related to unreliable power supply and inadequate sludge management in WWTPs (World Bank Group, 2017). Information regarding wastewater and faecal sludge production, treatment, and disposal in Nigeria is limited (World Bank Group, 2017). Faecal sludge disposal methods in Nigeria encompass treatment at designated facilities, burial in covered or open pits, and discharge into water bodies (FMWR et al., 2022; World Bank Group, 2018). Sometimes, sludge is dried on-site for subsequent use as feedstock for anaerobic digestion or in medical incinerators (World Bank Group, 2018). Due to the scarcity of information, the management of sludge at WWTPs in Nigeria remains largely undocumented, compounded by the suboptimal operational status of most plants. However, one operational facility in Nigeria utilises drying beds for sludge drying, with the dried sludge often accumulating within the facility and some portions utilised as manure (Saidu et al., 2019). Agricultural application and landfilling of sewage sludge are also practised in other WWTPs (Nikolopoulou et al., 2023). Furthermore, the suitability of sludge for use as fuel in steam and power generators was explored using the bio-drying technique (Navaee-Ardeh et al., 2010; Ogwueleka et al., 2021).

Likewise, treatment facilities in Nigeria are facing operational challenges primarily due to high energy and maintenance costs (FMWR et al., 2022; Solihu

& Bilewu, 2021). Decreased government funding for public utilities, compounded by an ageing infrastructure and limited technical expertise, has further exacerbated the situation (World Bank, 2021). Most WWTPs in Nigeria utilise conventional and mechanical systems that consume substantial energy, mainly relying on costly diesel generators (FMWR et al., 2022; Solihu & Bilewu, 2021). Moreover, there is a growing emphasis on integrating renewable energy sources into the country's electricity mix (Ayodele & Ogunjuyigbe, 2015). The Nigerian government has initiated plans to increase the share of renewable energy in the energy mix to 36% by 2030 through the Renewable Energy Master Plan, aimed at enhancing energy security and reducing the carbon footprint of the energy sector (ITA, 2021). Despite these efforts, the energy landscape in Nigeria remains inadequate, characterised by unreliable supply and outdated infrastructure. Nevertheless, the potential for energy recovery from sewage and resource recovery at WWTPs in Nigeria remains largely unexplored and under-researched.

The performance of WWTPs in Nigeria has been extensively studied to ensure compliance with regulatory standards (Ibangha et al., 2024), assess public health risks, and compare different treatment systems (Ogwueleka & Samson, 2020). These studies aimed to predict WWTP performance (Balogun & Ogwueleka, 2023) and evaluate their overall impact on environmental sustainability (Balogun & Ogwueleka, 2021). Research efforts have focused on assessing the efficiency of various treatment systems in removing organic and inorganic pollutants (Balogun & Ogwueleka, 2021, 2023; Okafor & Olawale, 2020). Unregulated activities at WWTPs pose significant risks to human health and the environment. While compliance with discharge standards has been extensively investigated in Nigeria, the broader environmental implications remain unclear. For instance, data on GHG emissions from WWTPs, crucial for addressing climate change concerns, are lacking.

Moreover, prior research has emphasised the lack of comprehensive studies on GHG emissions and the environmental footprint of water facilities in African cities (Diaz-Elsayed et al., 2020; Gallego-Schmid et al., 2019; Lam et al., 2020). This gap can be attributed to varying levels of awareness, resource limitations, and enforcement of policies and regulations (Karkour et al., 2021; Ogbu et al., 2023). Additionally, there has been a notable disparity in research distribution, with most studies focusing on Northern and Southern African regions, while West African countries, including Nigeria, remain underrepresented (Ogbu et al., 2023). Despite ongoing developments in LCA (Harding et al., 2021; Karkour et al., 2021; Maepa et al., 2017), information specifically related to the water sector, particularly in Nigeria, is currently lacking.

Therefore, in an effort to address the identified research gaps, this thesis proceeds as follows: Chapters 3 and 4 provide an extensive overview of the existing literature. Chapter 3 reviews recent LCA studies in Africa, synthesising the technical and methodological observed in the literature. It identifies the trends in the environmental impacts in the African region and explores the factors supporting them. Chapter 4 further quantifies the effects of selected factors on the outcome (e.g., energy use, GWP) of LCA studies. It uses statistical methods to collate existing studies in the literature, providing summary estimates for the outcome based on geographical location and feed water. Chapter 5 addresses the issue of quantifying wastewater generation, collection, and treatment in Nigeria. It presents a comprehensive analysis that combines various aspects, including the estimation of wastewater and sludge generation across different regions in Nigeria, technical viability assessment, and an in-depth evaluation of the economic feasibility of waste-to-energy technologies. Chapter 6 addresses critical gaps in understanding the efficiency, GHG emissions and energy use of a typical WWTP in Nigeria. It identifies mitigation strategies for reducing GHG emissions and improving the overall sustainability of WWTP operations. Chapter 7 assesses technologies for energy recovery at a WWTP. It explores technologies that harness energy from sludge and wastewater flow. The economic and environmental assessment of the technologies is investigated to identify a sustainable, cost-efficient option. Chapter 8 gives a general discussion of the results of the thesis. Lastly, Chapter 9 provides the summary conclusions.

2. Objectives

2.1 Main objective

The main objective was to assess the environmental and economic impacts of energy recovery options from wastewater treatment in Nigeria.

2.2 Specific objectives

1. To review and analyse current LCAs studies of WWT technologies in Africa.
2. To test flow and water quality characteristics and identify the potential environmental emissions at selected WWTPs in Nigeria.
3. To assess the economic feasibility of scenarios for resource recovery.
4. To evaluate scenarios for resource recovery using environmental impact tools such as life cycle assessment.

3. Comprehensive Review of Life Cycle Assessment Studies in Water and Wastewater Treatment

Adopted from: Ogbu, C.A., Alexiou Ivanova, T., Ewemoje, T.A., Alabi, H.A., Roubík, H. Towards Sustainable Water Management in Africa: A Comprehensive Review of Life Cycle Assessment Studies in Water and Wastewater Treatment. Submitted to International Journal of Life Cycle Assessment (IF: 4.8), Under review.

Abstract

Amid a global population surge, resource strain on facilities intensifies, magnifying competition for limited water resources. Life cycle assessment (LCA) evaluates the environmental impacts of products, processes, and services based on the net flow of energy, materials, and emissions during their life cycle. This review focuses on the state of LCA of water and wastewater treatment in Africa through an analysis of 70 scenarios from published articles. The articles were selected using the systematic review checklist of the standardized technique for assessing and reporting reviews of LCA. Strings of keywords were used to search for articles on the Web of Science, Scopus, and Google Scholar databases. Only original articles that assessed at least the water or wastewater treatment process using the ISO 14040 methodology were included. Case studies included were carried out in Africa. Over 70% of the studies originated from South Africa and Egypt, with a notable absence of representation from Nigeria. The operational stage of treatment processes was the most reported life cycle stage. Raw water, municipal wastewater, and acid-mine drains were commonly treated. Primary data on sludge characterisation was frequently absent. The ReCiPe and CML were the most popular methods. Potable water was recovered in 25% of the studies, soil conditioners 19%, energy 25% and others included minerals. Activated sludge process and ozonation had the highest environmental impacts. Global warming potential was the most influential impact category, and electricity generation from fossil fuels was the major contributor to adverse environmental impacts. The review emphasizes the need for increased data acquisition and storage, renewable energy use, and material recovery to offset environmental and financial costs in the water sector. It highlights the importance of integrating LCA into engineering design, engaging stakeholders in LCA, and establishing performance standards for green innovations. Future research and policy development to promote sustainable treatment practices are advocated.

Keywords

Environmental Impact; Energy Use; Carbon Footprint; Sustainability; Resource Recovery; Treatment Efficiency.

3.1 Introduction

The importance of sustainability in recent times has led to the reform of the sustainable development goals (SDGs) of the United Nations (UN Water, 2015). A sustainable environment suggests the measures put in place to protect the air, water, and land, as well as flora and fauna, and the interactions of these elements (UNDG, 2017). The SDG goal 6.3 targets the betterment of water quality through pollution mitigation. It also envisages halving the portion of untreated water while increasing recycling and reuse around the world by 2030 (UN, 2015a; UN Water, 2018). Moreover, global urbanization and population explosion have put much pressure on resources and facilities such as raw water and wastewater (WW) treatment facilities, respectively (WWAP, 2018). Population and rural-urban migration are escalating, which has huge implications for water management resources in major African cities (FAO, 2019). While Africa's population is predicted to hit a high of 42% in 2030 compared to its 1.19 billion population in 2015 (UN, 2015b), its urban population will increase by 60% by 2050 (Teye, 2018). According to the UN, the population of Nigeria, India, and China will account for 35% of the world's urban population growth by 2050 (UN, 2015b). Subsequently, the water withdrawal rate of Africa's top water consumers (Egypt, Nigeria, South Africa) has increased by approximately 9%, 15% and 31%, respectively, between the years 2002-2017, and within the same period, the population increased by 35%, 48%, and 19% while urban population increased by 25%, 101%, and 40% respectively (UN, 2015b). Unfortunately, the same increasing trend was evident in the generation of WW without a commensurate increase in treatment capacity (FAO, 2021a).

Similarly, Agriculture is a major consumer of water resources (FAO, 2023). Irrigation is an important factor for food security, and there is growing competition for available water resources (FAO, 2023). Fortunately, most projects have been implemented and designed to make use of treated WW, which meets the statutory irrigation water requirements to reduce competition while saving materials and energy for the treatment of potable water (FAO, 2021b). Some countries in Northern Africa and the middle east are faced with such herculean task (WWAP, 2015). While most developing nations have so far picked up the task of building and upgrading the water and wastewater treatment (W&WWT) plants for a variety of evolving reasons ranging from pollutant removal, water reclamation, nutrient recovery, biosolids agricultural application, and energy generation, same cannot be said about the developing nations nor the middle- and low-income nations predominant in Africa (WWAP, 2018). However, there is a rising interest in resources recovery from wastewater treatment (WWT) in Africa (Oertlé et al., 2020). However, these recovery processes have cost in terms of economic, social, and environmental concerns. In another dimension, through the vast implementation and experience of most developed nations, although WWT has its merits (Lam and Van Der Hoek, 2020), its operation could harm the environment through emissions into the air, land, and water (Nguyen et al., 2020; Song et al., 2020). Thus, the concept of sustainability assessment further strengthens the environmental regulations hitherto present in most countries. This assessment evaluates compliance with regulations, technological cost, and socioeconomic conditions as well as environmental impacts (EIs) of facilities, processes, and products (Corominas et al., 2020; Diaz-Elsayed et al., 2020).

The ISO 14040:2006 and 14044:2006 capture a sustainability method of the LCA. The LCA evaluates the EIs of products, processes, and services based on energy, materials (input and output), and emissions over their life cycle (Finkbeiner et al., 2006). Additionally, life cycle cost analysis (LCCA) is also an aspect that covers the evaluation of the financial implications of products and services over any given period of interest (Diaz-Elsayed et al., 2020). Broadly, these tools are encompassed under the life cycle thinking approach, which accounts for the economic (Diaz-Elsayed et al., 2020), environmental (Finkbeiner et al., 2006), and social impacts across all phases in the life cycle of a product or service (Corominas et al., 2020). Consequently, increasing awareness of sustainability issues and the need for appropriate LCA studies and reporting have been demonstrated in a recent review (Karkour et al., 2021) and others specific to African countries: Nigeria, Ghana, Ivory coast (Maepa et al., 2017); Egypt (Yacout, 2019); and South Africa (Harding et al., 2021) which is still far from what is obtainable in the developed world (Chen et al., 2014; Hou et al., 2015).

Nonetheless, the earliest review (Corominas et al., 2013a) that characterized studies on LCA of WWT showed the rate of adoption in developed and developing countries. Only one developing country, which was not from the African continent, was represented in the study. Recently, more LCA reviews studied 43 WWTPs in developing countries (Gallego-Schmid et al., 2019); 55 water reuse, 42 energy recovery, and 35 nutrient recoveries related to WWT (Diaz-Elsayed et al., 2020); and 65 WWT involving nutrient recycling (Lam et al., 2020). The representation from the African continent was five, three, and two, respectively. While the reason behind the low representation is still unclear, no review has aggregated these WWT-related LCAs in Africa to synthesize their outcomes for significant inferences and prospects. It is prudent to fill such a gap in the literature.

Therefore, in this review, an attempt was made to provide an overview of the LCA condition in W&WWT in the African region. The main aim is to identify the trends in the EIs of W&WWT and to explore factors supporting this trend (technical and methodological). The following questions are addressed, particularly in Africa:

a. What is the current extent of LCA implementation in W&WWT in published literature in Africa?
b. How does the implementation level in Africa compare with developed and developing countries?
c. What major gaps are identified in Africa, and how can they be addressed?

Firstly, the current available W&WWT LCAs in Africa are synthesized commenting on the technical and methodological parameters. Secondly, the LCA phases in the studies are examined in detail. Lastly, the pertinent outcomes in these studies are discussed from a continental and global perspective while synthesizing the limitations, challenges, gaps, and significance.

3.2 LCA studies on W&WWT in Africa

3.2.1 Data collection

For increased accuracy, this review adopted the systematic review checklist of the standardized technique for assessing and reporting reviews of LCA (STARR-LCA) (Zumsteg et al., 2012) designed in conformity with the preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement protocol (Alessandro Liberati et al., 2009; Shamseer et al., 2015). The theme of this review is to identify the trends in the EIs of W&WWT and to explore these trends (technical and methodological) using published LCA studies. Therefore, the articles selected are closely connected to this theme. Studies for this review were sourced from Scopus, Web of Science, and Google Scholar until December 2021. Firstly, thoroughly structured strings of keywords ((water OR wastewater OR Sludge) AND treatment) AND (life AND cycle AND assessment OR LCA)) pertaining to the theme were used to search for articles. A further search was done for studies carried out within or affiliated to African countries. This implied a complementary search of strings of keywords AND the top African countries by population, which gave 108 articles. The search string is given as ((lifecycle AND assessment) OR (life AND cycle AND assessment) OR LCA) AND (wastewater OR water OR sludge) AND treatment) AND ("South Africa") OR ("Egypt") OR ("Ghana") OR ("Kenya") OR ("Mali") OR ("Morocco") OR ("Uganda") OR ("Ethiopia") OR ("Congo") OR ("Tanzania") OR ("Algeria") OR ("Sudan") OR ("Nigeria") OR ("Angola") OR ("Mozambique") OR ("Madagascar") OR ("Cameroon") OR ("Ivory Coast") OR ("Niger") OR ("Burkina Faso")). After screening the title and abstract, twenty-six articles were removed comprising of duplicates, non-original research articles such as reviews and overviews, including other forms of publications such as project reports, conference proceedings, and non-English articles. Theses from higher institutions were removed since it is common practice that they are often published. The remaining eighty-two articles were moved to full-text screening. During the comprehensive review of full-text articles, fifty-nine were excluded, encompassing i) nine additional reviews, ii) one study conducted outside Africa, iii) thirty-six that did not address the treatment process, for instance, LCA of water reuse (e.g., for irrigation) without considering the treatment process, and iv) fifteen studies that focused on the technological and economic assessment of W&WWT but did not apply LCA.

Secondly, the reference lists of all selected studies were perused to find more LCA studies for inclusion. Four articles were included from additional reference materials sourced from reviews on LCAs in Africa (Felix, 2016; Harding et al., 2021; Karkour et al., 2021; Maepa et al., 2017) as well as other W&WWT LCA reviews (Diaz-Elsayed et al., 2020; Gallego-Schmid et al., 2019; Lam et al., 2020). Specifically, studies included must assess the treatment process and adopt the LCA methodology specified by ISO 14040:2006 and 14044:2006 (Finkbeiner et al., 2006). Studies that touched several elements of the water cycle and contained the treatment process were selected. Again, articles in which WW was treated together with other forms of waste were also incorporated. Papers that considered resource recovery from sewage or sanitation systems were also included. Finally, twenty-five articles were selected for this review because they met the inclusion criteria and, therefore, aligned with the theme of this review. Full-text screening, data extraction and management were performed using the trial version of the Covidence (Kellermeyer et al., 2018) review software. The data output from the software was in the form of a spreadsheet. This data was analysed to produce the information in subsequent sections represented by an overview in Table 1 and Figure 1

3.2.2 Overview of selected articles

An overview of the features found within each of the twenty-five selected articles containing seventy (70) scenarios is shown in Table 1. The elements in columns portray the technical data, methodological choices, and study typology that influence the outcome of LCA studies (Menten et al., 2013) and W&WWT LCAs (Li et al., 2021; Ogbu et al., 2023). Table 1 allows for comparison and analysis of the selected studies. For instance, the aim suggests the research question addressed, while the functional unit and phases considered depict the scope of each study. The software and LCIA method indicate the methodology used in each study. These elements are further discussed in the subsequent sections.

Out of about 54 African countries, only eight were featured in this study. Most of the assessments were carried out in South Africa (eleven articles) and Egypt (six articles). Nevertheless, this limited geographic coverage may not fully represent the diverse challenges faced by other African nations in WWT. Also, raises questions about the representativeness of the findings for the entire continent. The absence of studies from countries like Nigeria, Kenya, Ghana is noteworthy. For example, Nigeria has a GDP of 429 million USD, an urban population of over 107 million, and characterised by a withdrawal of 12.48 billion m^3/year from a total exploitable water of 59.51 billion m^3/year (FAO, 2022). Nevertheless, previous reviews (Karkour et al., 2021; Maepa et al., 2017) show that LCA application is evolving in Nigeria. Yet, the concentration of studies in South Africa and Egypt suggests that these countries may have more advanced WWT systems or research capabilities. Among the included studies, only four studies were published prior to 2011, while twenty-one were published until 2020, which shows a rapid rise in the implementation of such studies on the continent. This rise indicates growing awareness and interest in addressing WW issues on the continent. And the possible increase in the allocation of resources for research in related areas.

According to the (World Bank Group, 2019) classification of countries by income, thirteen studies were conducted in upper-middle-income (South Africa, Alegria), eight in lower-middle-income (Cameroon, Egypt, Morocco), and four in low-income (Somalia, Uganda, Ethiopia) economies, respectively. This reflects the diverse economic landscape in Africa and its impact on the available resources and technology for water purification in these localities. Low-income countries may require external support to develop adequate WW infrastructure. This underscores the need for tailored WWT solutions based on economic capacity.

3.3 Functional Parameters

3.3.1 Classification of feed solution treated

The most common type of treatment in the works under review is the urban WW (over 40% of the total), as shown in Figure 1.

Figure 1. Feed solutions found in the reviewed LCAs of W&WWT in Africa.

Table 1. Overview of LCA studies included in the review.

Country	Aim	Functional Unit	Phases considered	Software	LCIA method {nos. of EI reported}	Recovered resources	References
South Africa	Comparison of treatment methods for potable water production	1 m^3 of potable water	Construction, operation, demolition	GaBi	CML {8}	Potable water	(Friedrich, 2002)
South Africa	Assessment of system and identification of hotspots	1 m^3 of water supplied	Construction, operation	GaBi	CML {8}	Water	(Pillay et al., 2002)
South Africa	Assessment of urban water cycle	1 m^3	Construction, operation	GaBi	CML {8}	Potable water, recycled water	(Friedrich et al., 2009)
Egypt	Assessment of system improvement scenarios and associated burdens.	1 m^3/d	Operation	SimaPro	Eco-indicator 99 & 95 {11}	Biosolids	(Mahgoub et al., 2010)
South Africa	Comparison of desalination technologies	1000 ton/d 4% wt. salt	Operation	SimaPro	Impact 2002+ {3}	Salt, water	(Fernández-Torres et al., 2012)
Algeria	Assessment of water recycling technologies	5 L of recycled water	Construction, operation	SimaPro	Eco-indicators 95 {11}	Irrigation water	(Messaoud-Boureghda et al., 2012)
South Africa	Comparison of desalination technologies	1 m^3 boiler feed water	Operation	SimaPro	CML 2000 {6}	Water	(Ras and von Blottnitz, 2012)

Egypt	Assessment of improvement scenarios of a WWTP	1 m^3/d	Operation	SimaPro	Eco-Indicator 99 & 95 {11}	Fertilizers	(Roushdi et al., 2013)
Algeria	Development LCA based tool for system evaluation for potable water production	1 L of potable water	Construction, operation	SimaPro	Eco-indicator 99 {7}	Potable water	(Mohamed-Zine et al., 2013)
South Africa	Assessment of system advancement	100 tons dry tailings per d	Operation	SimaPro	ReCiPe, USEtox {7}	Acid, metals, water	(Broadhurst et al., 2015)
Egypt	Assessment and comparison of WWT technologies	1 PE/d	Construction, operation, demolition.	SimaPro	ReCiPe * {17}	Biosolids	(Risch et al., 2014)
Ethiopia	Comparison of treatment media	kg adsorbent for 8.5 mg/L fluorine removed	Operation	SimaPro	Eco-indicator, TRACI {14}	Water	(Yami et al., 2015)
Cameroon	Assessment of EIs of sanitation systems	500 L/person/yr.	Construction, operation	-	- {12}	Organic manure	(Aimé et al., 2016)
Uganda	Evaluation of impacts of water supply sources and treatment methods at household levels	3.57 L of potable water	Operation	SimaPro	- {11}	-	(Prouty and Zhang, 2016)

South Africa	Evaluation of mixed waste treatment systems and impact reduction	1 kg of live weight/ carcass	Operation	SimaPro	CML-IA-baseline {3}	Organic manure, electric, thermal power	(Russo and von Blottnitz, 2017)
South Africa	Comparison of conventional and non-conventional systems	2 kg human faeces, 14.2 kg urine per d	Construction, operation	SimaPro	ReCiPe method endpoint & hierachist {3}	Ash, energy, sludge. Compost, sanitized urine,	(Anastasopoulou et al., 2018)
South Africa	Improvement analysis of acid mine drain treatment process	1 m^3 of effluent	Construction, operation	SimaPro	ReCiPe 2008*, IPCC 2013 {18}	Water, sludge	(Masindi et al., 2018)
Uganda	Assessment of integrated system	897 tons biowaste /yr.	Operation	GaBi	CML 2001 {3}	Biogas, manure, briquette, electricity, heat	(Agunyo et al., 2019)
Egypt	Improvement analysis of conventional WWTP	1 m^3 of treated WW	Construction, operation	-	CML 2000 {8}	Sludge, water, biogas	(Awad et al., 2019)
South Africa	Comparison of water treatment processes for potable water production	1 m^3 of potable water	Construction, operation	SimaPro	ReCiPe midpoint {18}	Potable water	(Goga et al., 2019)
Somalia	Assessment of system profiles, hotspots identification, and correlation between	1 L	Construction, operation, demolition	OpenLCA	ReCiPe 2008, Endpoint (H) {17}	Potable water	(Rossi et al., 2019)

	efficiencies and diseases.						
Morocco	Assessment and comparison of WWT systems	1 PE; 60 g BOD_5/d	Construction, operation	ACV4E	ReCiPe midpoint 2014 {18}	-	(Bahi et al., 2020)
South Africa	Assessment of system and identification of hotspots	1 L of WW	Operation	SimaPro	ReCiPe 2016 {2}	Nitrogen, Phosphorus	(Mavhungu et al., 2021)
Egypt	Assessment of WWTP upgrade	1 m^3 of treated WW	Construction, operation, demolition	GaBi	ReCiPe {13}	Water, manure, biogas	(Morsy et al., 2020)
Egypt	Assessment of the feasibility of system upgrade	1 m^3	Construction, operation	SimaPro	ILCD 2011 Midpoint {16}	Water	(Pinelli et al., 2020)

*-midpoint & endpoint; EI- impact categories; PE- person equivalent; n. a.- not available

A greater part of the urban WW was from municipalities, while a smaller portion was a campus treatment scheme where WW is mixed with organic waste for treatment (Agunyo et al., 2019). Urban effluents are made up of a combination of flows from sewerage networks in residential areas, industries as well as rainfall runoffs. Treatment of domestic WW was the case in two studies (Aimé et al., 2016; Anastasopoulou et al., 2018).

The evaluation of industrial effluents was found in six articles, dominated by saline and mine WWT in South Africa. Mine WW containing varying degrees of salinity (Broadhurst et al., 2015; Fernández-Torres et al., 2012; Masindi et al., 2018), and others mixed with seawater (Goga et al., 2019) were evaluated. Effluents from the slaughterhouse were evaluated in South Africa (Russo and von Blottnitz, 2017). Additionally, raw water from dams, wells and surface water were considered mainly for the provision of potable water in varying settlements in Somalia, Uganda, Ethiopia, South Africa, and Algeria (Friedrich, 2002; Mohamed-Zine et al., 2013; Prouty and Zhang, 2016; Ras and von Blottnitz, 2012; Rossi et al., 2019; Yami et al., 2015). In this study, WWT-related LCAs were dominated (over 90%) by urban or domestic WW, which aligns with over 90% in developed nations (Corominas et al., 2013a) and 70% in developing nations (Gallego-Schmid et al., 2019) in other reviews.

The prevalence of urban WWT reflects Africa's ongoing urbanization and population growth (WWAP, 2018). Urban centres in Africa are grappling with the challenges of managing and treating wastewater effectively. Additionally, the complexity from mixed effluents and diverse pollutants requires tailored WWT strategies that consider local conditions and pollution sources (Ravina et al., 2021). However, the popularity of raw water treatment (WT), mainly for providing potable water in various settlements across Africa, indicates the importance of water quality and access in the continent (FAO, 2017). This underscores the urgency of addressing urban water resources management in Africa. Hence, to accommodate this trend, sustainable water resource management is a noteworthy priority for policy makers (Elkin and Katz, 2019). Furthermore, the concentration of industrial wastewater studies, such as in South Africa, suggests that certain regions in Africa might have significant industrial activities that generate specialized wastewater streams. The presence of industrial effluents highlights environmental challenges associated with industrialization. The management of such streams is crucial due to their unique characteristics and potential EIs. The strengthening of environmental regulations and monitoring can mitigate these potential pollution sources (WWAP, 2018).

3.3.2 Characterization, Pollutant Removal, and Resources recovered

3.3.2.1 Characterization and pollutant removal efficiency

In W&WWT there are certain parameters often considered in other to ascertain the percentage of pollutant removal by a treatment system. In WWT LCAs BOD, COD, TSS, TP, TN were the most reported, while TSS and turbidity for raw WT. However, not all stated data were primary measurements in these studies. The BOD and COD were reported in six (i.e., <35% of WWT) articles. The BOD ranged from 529 (in stormwater and municipal WW) to 50 mg/L. The mean of BOD and the rate of removal achieved in the treatment of urban WW in this analysis were 314 mg/L and 70%, respectively. Similarly, COD ranged from 72 to 838 mg/L, averaged at 546 mg/L, with a mean removal rate of 63% for urban WWT. Likewise, TSS was indicated in eight articles (six WWT and two WT). The average influent TSS for urban WWT was 767 mg/L, with a mean removal of 75%. Similarly, the influent TP and TN were stated in four and five articles, respectively. The range, mean, and mean removal values for TP and TN were 23 to 0.2, 9 mg/L, 52% and 239 to 38.4 mg/L, 71 mg/L, 64% for urban WWT, respectively. Other occasionally indicated parameters include pH, total dissolved solids, coliform count, and ammonia. However, contaminants of emerging concern that are not a compulsory part of LCA but gained relevance in recent times were not considered in any of the reviewed studies, which are consistent with the assertions of Corominas et al. (2020).

The distribution of the influent and effluent parameters of urban WWT LCAs in Africa is represented in Figure 2. Effluent concentrations are generally lower than influent concentrations, indicating the effectiveness of WWT processes. Variability is evident across different WWTPs and parameters, highlighting the diverse nature of wastewater sources and treatment technologies. Similarly, the mean values suggest a pattern where TSS > COD > BOD. The concentration of TSS in the influent of WWTPs is greater than the concentration of COD. This is because TSS comprise both organic and inorganic particles that may be carried by wastewater, such as dirt, trash, and other solid items.

Nonetheless, COD, is the total organic and inorganic content in the wastewater, including both dissolved and suspended components (EPA, 2004). COD in WWTP influent is often greater than BOD because COD comprises both biodegradable and non-biodegradable organic matter, whereas BOD only measures biodegradable organic matter that may be metabolised by microbes. Higher COD levels are caused by non-biodegradable organic waste, such as some industrial chemicals or complex organic molecules (EPA, 2004). The variability in influent and effluent concentrations emphasizes the complex nature of WWT in Africa. While certain WWTPs demonstrate effective pollutant removal, others struggle, likely due to differences in treatment technologies, flow rate, equivalent population dilution factor, and plant layout (Longo et al., 2016; Wakeel et al., 2016). The living standard, demographic and geo-morphological attributes of the locations, and regulatory frameworks also have an influence (Cardoso et al., 2021; Li et al., 2021). This emphasizes the importance of advancing WWT practices across Africa to reduce EIs.

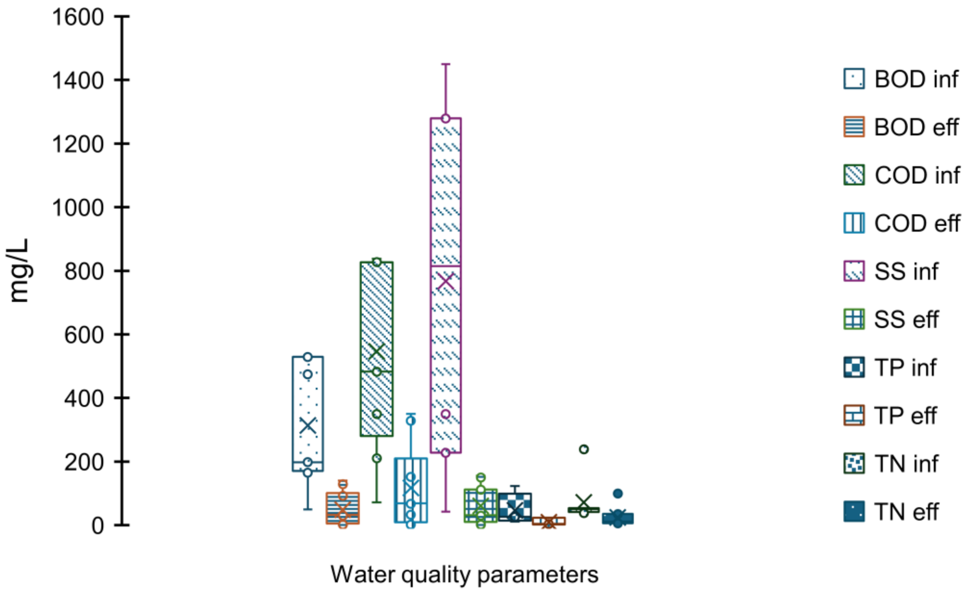

Figure 2. Comparison of pollutants in influent (inf) and effluent (eff) of LCAs of urban WWT in Africa.

In comparison with results from analyses of developing and developed nations, the average parameters of urban WW assessed in Africa show higher values. The influent BOD, COD, TSS parameters in developed countries (Corominas et al., 2013a) were often higher than those of developing countries (Gallego-Schmid et al., 2019), which contrasts the observations in this study. This could be attributed to the small number of studies considered. In particular, the largest contributor to these high values is urban WWT in Egypt (Pinelli et al., 2020), comprising untreated municipal and industrial WW, and excess irrigation water (containing fertilizer and pesticides). However, the cumulative average removal efficiency corresponds to what is obtainable in developing countries. The pollutant removal efficiency in developing countries was demonstrated to be lower than in developed nations (Gallego-Schmid et al., 2019). Also, the nature, type, quantity, legal requirements are critical to the removal efficiency and treatment levels in various countries (Ahmad et al., 2020). The high remediation can be attributed to advanced treatment technologies and levels in developed countries owing to very stringent discharge requirements.

In most African nations, the fraction of raw WW discharged into the environment is large, implying a higher risk of eutrophication (FAO, 2022). The emission criteria from African treatment facilities are less strict, and adherence is poor as opposed to developing nations. Similarly, there are disparities between the effluent discharge guidelines among African nations (Kayode et al., 2018). For example, a study showed how the BOD requirement varied from 30-50 mg/l in Nigeria to 30 mg/l in Tanzania; and DS from 3000 mg/l in Tanzania to 200 mg/l in Nigeria (Kayode et al., 2018). These irregularities in effluent characteristics reflect in the EI categories of the treatment facilities. The linkages between effluent characteristics and potential impact categories have been established (Corominas et al., 2020). Climate change and global warming potential (GWP) are associated with Nitrogen, BOD, and COD. Eutrophication is influenced by Nitrogen (in form of NH_4^+, NH_3), Phosphate (PO_3^{-4}), and BOD. Likewise, micropollutants, including heavy metals, are related to human toxicity and ecotoxicity, while Sulphur (in H_2S form) contributes to acidification and human toxicity (Corominas et al., 2020).

3.3.2.2 Sludge management and Resources recovered

Sludge management cannot be overlooked due to EIs related to toxicity by heavy metals and recalcitrant contaminants often contained in the sludge. Sludge characterization was indicated in four studies, while only one (Aimé et al., 2016) involved data from primary measurements, the other 3 studies (Agunyo et al., 2019; Mahgoub et al., 2010; Roushdi et al., 2013) alluded to data from the literature. The study by Hospido et al. (2005) was often cited in the studies in question. Parameters mostly indicated under the characterisation of sludge were Copper, Lead, Zinc, Cadmium, Nitrogen (in the form of TN or Total Kjeldahl Nitrogen), phosphorus, potassium, while others include Platinum, Chromium, COD, Nickel. Sludge characterisation is often important due to its indication of the suitable final disposal of the residues or proper resource recovery strategy. Figure 3 shows the common methods used in sludge treatment and disposal as well as the composition of the resource recovery regimes in the articles under review.

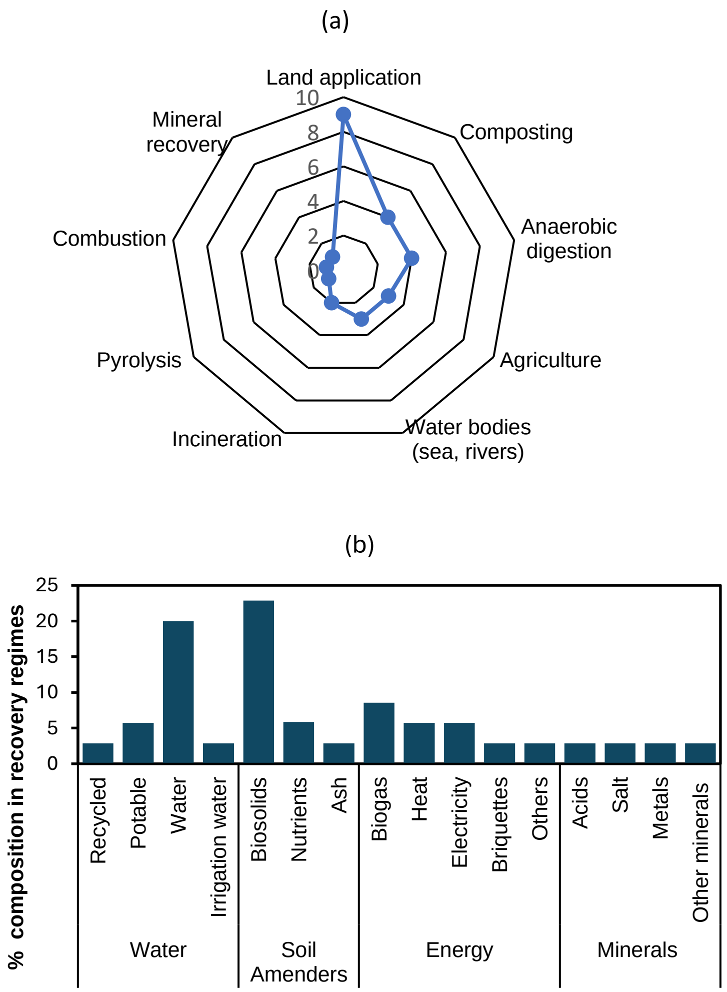

Figure 3. Representation of sludge management/disposal methods (a) and resource recovery in WWT (b) for LCAs in Africa.

The most prevalent type of sludge management technique in the reviewed WWT articles is land application (over 30% of total occasions) related to landfilling, burial, open dumping, and unspecified disposal incidents. Other common methods include composting (14%), anaerobic digestion (14%), agricultural land application (10%), and disposal into sea and rivers (water bodies) (10%). Other forms of treatment are shown in Figure 3(a). In addition to effluent discharged back into nature (classified as water) in Figure 3(b), only seventeen studies reported the recovery of resources. The recovery regime constituted 35 instances, while the frequently recovered resources include biosolids (over 22% of total cases) and biogas (over 8%).

As demonstrated by the low implementation, performing sludge characterization in Africa might be challenging owing to limited funds, technical skills, and equipment for complete characterisation (Akwo and Hjelmar, 2008). Also, malfunctioning and inadequate treatment facilities impede data collection (Akwo and Hjelmar, 2008). Hence, limited precise data make detailed sludge characterisation difficult (Aranda Usón et al., 2012). Moreover, regulations ban sludge landfilling in several regions (Przydatek and Wota, 2020), while others mandate its inclusion in LCAs as demonstrated in the European Union guidelines (European Union, 2023). This is attributed to the heavy metal and pathogenic content of sludge, which poses health and ecological risks especially due to the application of sludge in landfills, farmlands and dumping into water bodies. Therefore, the emissions of these pollutants are influenced by the sludge characteries and in-situ properties of the soil and water bodies which should be accounted for instead of adopting data from different countries where these conditions defer.

3.3.2.3 Treatment capacity and functional life

Treatment capacity is a key factor since the scale of treatment is inversely proportional to energy consumption, while the treatment level is directly proportional to electricity consumption (Diaz-Elsayed et al., 2020). This parameter was reported in thirteen out of the twenty-five studies reviewed. The largest plants (>500000 m^3/d) are in Egypt employed for the treatment of urban WW. In some cases, there was a lack of clarity between treatment capacity and FU, e.g., the treatment of household sewage (Anastasopoulou et al., 2018) and industrial slurry (Broadhurst et al., 2015) in South Africa and Cameroon for latrines (Aimé et al., 2016). Table 2 shows the different scales of treatment and the number of reviewed studies that fall under each category. Functional life is relevant for the modelling of the LCA of processes, as discussed in section 4. It is another crucial part of the life cycle stages as it plays a vital role on the eventual impact of the WWT (Corominas et al., 2020). This metric was reflected in less than 20% of the analysed LCAs, and it varied from fifteen (Rossi et al., 2019), twenty (Aimé et al., 2016; Masindi et al., 2018) to thirty (Awad et al., 2019; Pillay et al., 2002) years. The variation suggests that the choice of life span slightly correlates with the size and type of the systems since there was an increase in lifetime from bench and pilot scale to larger scale facilities.

Table 2. Classification of treatment scale (adapted from De Haas et al. (2015)).

Size Class	PE Range	Capacity (m^3)	References
1	≤ 1000	≤ 200	(Aimé et al., 2016; Anastasopoulou et al., 2018; Broadhurst et al., 2015; Masindi et al., 2018; Messaoud-Boureghda et al., 2012)
2	1001 - 5000	200 - 1000	(Pinelli et al., 2020)
3	5001 - 10000	1000 - 2000	(Bahi et al., 2020)
4	10000 -100000	2000 - 20000	
5	> 100000	> 20000	(Awad et al., 2019; Goga et al., 2019; Mahgoub et al., 2010; Mohamed-Zine et al., 2013; Morsy et al., 2020; Roushdi et al., 2013)

PE – population equivalent

3.3.2.4 Treatment technologies

As stated previously, most of the articles assessed the treatment of urban WW, and in most cases (five out of eleven), the activated sludge (AS) process was considered. The AS was evaluated for urban WWT in Egypt (Awad et al., 2019; Morsy et al., 2020; Risch et al., 2014; Roushdi et al., 2013) and South Africa (Friedrich et al., 2009). These systems were often preceded by screening, grit removal, and primary clarification, then secondary clarification. In some cases, AS was coupled with the phosphate elimination process in Egypt (Risch et al., 2014), and in other cases, tertiary treatment such as chlorination (Awad et al., 2019; Morsy et al., 2020) and microfiltration (Roushdi et al., 2013). Furthermore, the matter of concern was urban reuse of water (Awad et al., 2019), effluent quality for reuse in agriculture (Morsy et al., 2020), water consumption during treatment (Risch et al., 2014), and overall system efficiency (Roushdi et al., 2013).

Decentralized systems were the key subject in eight papers. For the treatment of urban WW, in Morocco, Bahi et al. (Bahi et al., 2020) evaluated clarification followed by anaerobic ponds, whereas Aime et al. (Aimé et al., 2016) studied latrine in rural areas of Cameroon. In Egypt, rapid sand filtration and chlorination were considered by Mahgoub et al. (2010). Pinelli et al. (2020) analysed constructed wetlands and facultative lagoons, while Agunyo et al. (2019) examined anaerobic co-digestion with organic waste in Uganda. For domestic WWT in South Africa, Anastasopoulou et al. (2018) considered nano membrane toilet, pour flush toilet, and urine diverting dry toilet systems. Advanced treatments like reverse osmosis (RO) in combination with microfiltration and biological filters (Messaoud-Boureghda et al., 2012) in Egypt, and Struvite precipitation (Mavhungu et al., 2021) in South Africa were also assessed.

Industrial WWT often featured non-conventional systems. For example, RO in combination with ultrafiltration for the treatment of sea and mine water (Goga et al., 2019), low salinity industrial effluent (Ras and von Blottnitz, 2012). Additionally, Ras and von Blottnitz (2012) evaluated demineralization, sodium and hot lime softening, (Broadhurst et al., 2015) assessed desulfuration floatation for tailings slurry stream treatment, while Fernandez-Torres et al. (2012) adopted evaporative crystallization and eutectic freeze crystallization for saline mining effluents. Masindi et al. (2018) studied raw mine WT by magnesite, lime, soda ash treatment and CO_2 bubbling. For industrial WWTP effluent, Pillay et al. (2002) studied filtration, ozonation, activated carbon filtration, and chlorination, whereas Russo & von Blottnitz (2017) assessed lagooning and anaerobic digestion for slaughterhouse.

For WT, solar pasteurization was evaluated in Somalia (Rossi et al., 2019), and fluoride adsorption in Ethiopia (Yami et al., 2015). Other treatment systems for raw water included variations of filtration and disinfection either in combination with heating (Prouty and Zhang, 2016), or Iron oxidation and adsorption (Mohamed-Zine et al., 2013), or clarification and ozonation (Friedrich, 2002). Advanced treatment technologies were shown to emerge either for production of potable water from impoundments (Friedrich, 2002; Mohamed-Zine et al., 2013; Yami et al., 2015) and industrial effluents (Friedrich et al., 2009; Goga et al., 2019; Pillay et al., 2002), or recycling for industrial (Ras and von Blottnitz, 2012) and urban (Messaoud-Boureghda et al., 2012) reuse. To meet such high effluent qualities, one or a combination of these systems are employed, namely membrane filtration, ultrafiltration, microfiltration, adsorption, and ozonation.

3.4 LCA Framework Phases

The selected articles were examined to gather information related to methodological choices and assumptions. The method for conducting LCA is according to ISO standards, which is divided into four phases: goal and scope definition, life cycle inventory (LCI), life cycle impact assessment (LCIA) and interpretation. However, the focus of the goal and scope definition lies on the FU and Life cycle stages, for the LCI phase is focused on data sources and databases, the LCIA centres on the model, the level, and the categories considered. For the interpretation phase, the emphasis is on sensitivity analysis, literature comparison and limitation.

3.4.1 Goal and Scope definition

The various purposes for conducting LCA of water purification facilities and the pertinent scopes have been highlighted in previous studies (Corominas et al., 2020; Rashid et al., 2023). In this review, the comparative assessment of technologies and assessment of system improvement dominated the overall goals of the reviewed studies. For instance, the EIs, efficiency, and sustainability of technologies for sanitation (Anastasopoulou et al., 2018) and desalination (Ras and von Blottnitz, 2012) were compared. Certain studies focused on assessing the environmental performance of existing treatment systems and identifying opportunities for improvement (e.g., (Agunyo et al., 2019; Morsy et al., 2020)), and the feasibility of system upgrades or alternative approaches (e.g., (Bahi et al., 2020; Pinelli et al., 2020)). The overall assessment for hotspots identification and the potential for impact reduction was the aim of other studies (Goga et al., 2019; Risch et al., 2014).

Also, LCA can be employed at various levels at water facilities, which include planning, design, operation, and new technology development levels (Corominas et al., 2020). Firstly, it aids in strategic planning by comparing different management approaches and evaluating long-term scenarios. For instance, a study in Cameroon assessed the sanitation systems in a neighbourhood with spontaneous housing (Aimé et al., 2016). Secondly, LCA informs the design phase, identifying potential hotspots. Various designs of treatment systems were assessed and compared in studies under review. In South Africa, nano membrane toilet (NMT) system, pour flush toilet (PFT) system, urine diverting dry toilet (UDDT) system, UDDT+ composting were compared (Anastasopoulou et al., 2018), evaporative crystallisation (EC) and eutectic freeze crystallisation (Fernández-Torres et al., 2012), and RO, and RO+ ultrafiltration were assessed for treatment of industrial wastewater (Goga et al., 2019). Thirdly, LCA optimizes existing systems and guides operational decisions. Hence, the optimization of operation, and evaluation of potential retrofitting options of treatment systems were investigated in various studies (Masindi et al., 2018; Ras and von Blottnitz, 2012; Russo and von Blottnitz, 2017). Lastly, several studies focused on understanding the environmental performance of new technologies and their potential improvements (Friedrich, 2002; Rossi et al., 2019). Lastly, other LCA studies were done as a combination of several levels of assessment. The study of adsorbents for WT in Ethiopia (Yami et al., 2015) suggests aspects of design level comparison and technology development.

Though there are examples from all levels, indicating a comprehensive approach to wastewater LCA in Africa, the situation may differ from other developing and developed nations due to variations in infrastructure, regulations, resources, and socio-economic factors (Harding et al., 2021). However, the common goal of assessing EIs, and resource use is universal. Nevertheless, the context, challenges, and priorities can vary between countries. Developed nations may focus on optimizing advanced treatment technologies and resource recovery in their LCA studies due to the availability of resources and infrastructure (Diaz-Elsayed et al., 2020; Lam et al., 2020). In contrast, developing nations prioritize simple and low-cost technologies that can be implemented with limited resources and still achieve meaningful environmental benefits (Gallego-Schmid et al., 2019). Developed and developing nations have different priorities in their LCA studies, with the former focusing on energy efficiency and advanced methods, while the latter prioritize cost-effective solutions. Nonetheless, both types of studies contribute valuable insights, while considering local contexts and challenges in the application of LCA (Diaz-Elsayed et al., 2020; Gallego-Schmid et al., 2019). The ultimate approach to wastewater LCA in this review aligns with global practices, emphasizing sustainable, efficient, and environmentally friendly wastewater management. Practitioners in Africa focus on understanding the implications of different treatment technologies and enhancing the performance of existing systems. This indicates an emphasis on finding sustainable and context-appropriate solutions for W&WWT, given the challenges many African countries face in terms of water scarcity, inadequate infrastructure, and limited resources. LCA studies are likely aimed at identifying cost-effective and environmentally friendly approaches to meet WT needs.

3.4.1.1 Functional Unit

The FU is a measure of the quantification of the identified performance of a product or process. This is often expressed in the majority of water related articles as any of volume, volume by a treatment purpose, or person equivalent (specified as the total composition of mass and flow generated daily per person).

From the articles under review, the volume basis was often used (seventeen out of twenty-five), followed by the objective (six in twenty-five) of the treatment and person equivalent (PE) (two out of twenty-five). However, several studies have criticized the use of only volumetric reference as it does not reflect the treatment efficiency of the system. To address this, Gallego-Schmid et al. (2019) recommend the PE, while Byrne et al. (2017) suggest both water quantity (volume, catchment area, PE) and management (quality and flow) components. For WW and drinking water, FU should reflect volume, PE, and quality (Byrne et al., 2017). In the studies that used PE as FU, Bahi et al. (2020) considered a treatment of PE equivalent to 60 g BOD_5, while Risch et al. (2014) focused FU on the treatment of organic load from one PE which meets the European discharge standard. Other FU featured by-product outputs like ton of salt (Fernández-Torres et al., 2012), dry tailings (Broadhurst et al., 2015) recovered, kg of meat and carcass produced (Russo and von Blottnitz, 2017). However, others examined services rendered like number of households (Friedrich et al., 2009) or adults served (Anastasopoulou et al., 2018), tons of organic waste managed (Agunyo et al., 2019), while Yami et al. (2015) expressed FU in terms of the quantity of absorbent needed to meet certain removal efficiency. Finally, not many studies (Risch et al., 2014; Yami et al., 2015) considered the effluent quality in the FU. Hence, none of the studies met the volume, PE, and quality requirements proposed by Byrne et al. (2017).

3.4.1.2 Life cycle stages

In the case of system boundaries in LCA of WWT, it is often expressed based on wastewater or the treatment facility as a product (Corominas et al., 2020). When considering WWT as a product, the conventional boundary is from its source through the treatment line up to the effluent (and occasionally sludge) disposal. This is often expressed as cradle-to-grave. However, when the treatment facility is considered a product, the construction, operation, and demolition (end of life) stages suffice (Corominas et al., 2020). As in other reviews, all the LCAs examined included the operational stage of the treatment process (Gallego-Schmid et al., 2019). However, a lower percentage quantified the impacts of construction (60%) or end of life (16%), either because a comparison was undertaken using LCA (e.g., (Fernández-Torres et al., 2012)) and similar processes were ignored accordingly or these stages were presumed to be negligible (e.g., (Agunyo et al., 2019)). Overall, both construction and operation were considered in 44% of the papers (e.g., (Goga et al., 2019; Pinelli et al., 2020)) while only 16% considered the entire construction, operation, and demolition stages (e.g., (Morsy et al., 2020; Rossi et al., 2019)) as shown in Table 1.

The impacts of the construction stage were significantly higher compared to the operation stage in studies that included the construction stage of a natural lagoon (Bahi et al., 2020), latrines (Aimé et al., 2016), wetlands (Pinelli et al., 2020), and solar pasteurization systems (Rossi et al., 2019). Specifically, in the assessment of the impacts of latrine systems in Cameroun, the acquisition of the construction materials had the ultimate impact (Longo et al., 2016). Similarly, solar collector production had the greatest impact on the solar treatment system implemented in Somalia (Deng et al., 2010), while the potential toxicity of excavation and limestone materials was of greater concern in the construction of instream treatment systems in Egypt, whereas in other studies the construction stage merely showed impact (Awad et al., 2019; Rossi et al., 2019) while contributing 25-30% (Messaoud-Boureghda et al., 2012) and as low at 0.44% (Masindi et al., 2018) to the overall impact. Other studies in the literature suggest that the impact of the construction phase range from 5-50% (Corominas et al., 2020; Morera et al., 2017) effect on the whole environmental load of extensive technologies and large plants. Another research narrowed on variations resulting from system boundaries (Ogbu et al., 2023).

Though most studies failed to include the construction and decommissioning stages, the decision was influenced by the goal of the LCA studies and the nature of the treatment facility. However, it is recommended to include the construction stage when decisions regarding construction materials are critical (Simões et al., 2011), for facilities with minimal operation and maintenance requirements (Byrne et al., 2017), or passive systems with low energy use intensity (Corominas et al., 2020). Thus, the smaller the treatment system's capacity and energy requirement, the more significant the impact of the construction stage (Boehm et al., 2019). This characterises the treatment systems obtainable in developing nations, where low cost and easily maintained technologies are employed due to abundant land (Gallego-Schmid et al., 2019).

The operation stage was the chief contributor to total EIs in the majority (80%) of the studies. Unit operations that are typically emphasised comprise electricity generation (from fossil fuels) (Goga et al., 2019; Masindi et al., 2018; Morsy et al., 2020; Russo and von Blottnitz, 2017), and chemical usage (Goga et al., 2019; Masindi et al., 2018). These were attributed to highly engineered and resource-intensive technologies in water purification. The production of portable water consumes more energy than the treatment of industrial and municipal wastewater, respectively (Longo et al., 2016). Due to the level of purification required and the nature of pollutants to be removed, the technologies employed in the treatment of potable water are energy intensive (Longo et al., 2016). Similarly, industrial wastewater often contains recalcitrant contaminants that might require unconventional, and energy consuming technologies compared to municipal WWT. The technologies associated with high energy consumption include RO, ultrafiltration (Goga et al., 2019; Ras and von Blottnitz, 2012), membrane filtration (Friedrich, 2002), ion exchange and softening (Ras and von Blottnitz, 2012), eutectic freeze crystallization and evaporative crystallization (Fernández-Torres et al., 2012), mostly for treatment of saline water. Meanwhile, for WWTPs, energy use decreases in larger facilities since they are often automated and under stable conditions (Li et al., 2021; Longo et al., 2016). Also, the AS tend to consume more energy compared to anaerobic/anoxic/oxic and anoxic/oxic processes (Longo et al., 2016), while the membrane reactor (MBR) consumes the most energy in comparison to biological nutrient removal (BNR) and AS because of the energy requirement of aeration units and losses owing to fouling and clogging (Longo et al., 2016).

Similarly, the high dependence on fossil fuel (Goga et al., 2019; Masindi et al., 2018; Morsy et al., 2020) such as coal (Friedrich et al., 2009; Ras and von Blottnitz, 2012) for electricity was the subject of concern in most studies. Up to 90% and 76% of energy and electricity, respectively, consumed in Africa are sourced from oil, gas, and coal. These sources consequently contribute about 92% of CO_2 emissions from fuel origin in Africa. Emissions from coal are dominated by South Africa and Morocco, while Egypt, Algeria and Nigeria are key emitters of CO_2 from oil and gas. Several studies have shown a positive linear relationship between energy use and greenhouse gas (GHG) emission intensity (Lee et al., 2017; Longo et al., 2016). These may explain the high GWP values from higher from South Africa and Egypt. However, indirect emissions constitute 14-68% of total GHG emissions from treatment facilities, originating primarily from energy consumption during aeration, pumping, wastewater, and sludge transportation.

End of life processes related to sludge disposal (Agunyo et al., 2019; Bahi et al., 2020), waste (Aimé et al., 2016; Anastasopoulou et al., 2018), pollutants in the effluent (Bahi et al., 2020; Mahgoub et al., 2010; Morsy et al., 2020) were subject of concern. Although only four studies considered sludge characterisation, several studies considered sludge disposal. Certain conventional LCA practices associated with sludge management were implemented, albeit minimally. For instance, the extension of the system boundaries to account for the positive effects of the nutrient value of manure by substituting chemical fertiliser (Mavhungu et al., 2021; Morsy et al., 2020), mineral recovery (Masindi et al., 2018), energy (Agunyo et al., 2019) as depicted in Figure 3 and CO_2 offsetting (Agunyo et al., 2019; Pinelli et al., 2020).

3.4.2 Life Cycle Inventory

The content of the LCI is often a product of the goal and system boundaries defined in the early stages of the assessment framework (Finkbeiner et al., 2006). This phase constitutes the categorization and quantification of input and out of material, energy, chemicals, waste, and emissions (Finkbeiner et al., 2006). The LCI phase complies with the necessary data across the system boundary to meet the goal of the LCA study by evaluating these data in relation to the FU (Corominas et al., 2020). In this study, about 67% applied data from primary measurements, while others were either undefined or vague. Data was sourced from primary measurements, reports (Masindi et al., 2018), and calculations (Agunyo et al., 2019). The inventory was adequately explained in terms of sources and in relation to the system operation in 83% of studies (Fernández-Torres et al., 2012; Roushdi et al., 2013). Also, the inventory was available in text or supplementary information in 70% of the studies (Fernández-Torres et al., 2012; Roushdi et al., 2013). Most papers (58%) had data as a main limitation. There was a lack of specific background data as only one study reported the use of local data (Friedrich et al., 2009). Other sources of background data were LCI databases provided by Ecoinvent and Gabi, literature, and calculations. While Team 3 database and unspecified generic datasets appeared in some studies (Friedrich et al., 2009).

Making inventory data accessible is crucial for the transparency and reproducibility of LCA studies (Corominas et al., 2020). The quality and comprehensiveness of the LCI data directly impact the accuracy and reliability of the impact assessment phase. The data collected in the LCI phase are used to quantify EIs. However, it was also clearly visible that the reproducibility of most of the studies was called into question because just naming or mentioning the database or the reference from the literature is not specific enough. Moreover, background data for the electricity mix were often unspecified or adapted from Europe (Agunyo et al., 2019; Pillay et al., 2002). Some studies also adapted other key data, such as Indian diesel production (Agunyo et al., 2019) from the literature. Others stated data was taken from the literature (Awad et al., 2019; Mahgoub et al., 2010).

The average electricity consumption for raw WT in Africa from this study ranges between 1.91-2.16 kWh/m^3 against 0.07-8.5 kWh/m^3 in developed countries (Gallego-Schmid et al., 2019; Plappally and Lienhard V, 2012). WWT consumes about 0.3-0.51 kWh/m^3 compared to 0.38-1.22 kWh/m^3 in developed countries (Gallego-Schmid et al., 2019; Plappally and Lienhard V, 2012). Developed countries tend to have higher energy consumption in water and WWT facilities due to stringent standards and advanced technologies. They also have the capacity and incentives to invest in energy-efficient measures (UN Water, 2015). In contrast, lower energy consumption in water and WWT facilities in Africa can be attributed to factors like limited energy access, simplified treatment processes, and resource constraints (UN Water, 2015).

3.4.3 Life Cycle Impact Assessment

This phase uses the LCI results to estimate the consequences of potential EIs. The estimation process involves linking LCI data to particular EI categories and category indicators, thus trying to understand these impacts. Information obtained during this phase is important for the interpretation phase (Finkbeiner et al., 2006).

3.4.3.1 Impact assessment methods

The choice of methodology is fundamentally influenced by the aim of the research. Endpoint and midpoint impact indicators attempt to characterise human and environmental health impacts, but the alignment of the emission conversion to the locality of the system under consideration remains a subject of debate (Byrne et al., 2017). Typical endpoint methodologies applied were ReCiPe, Eco-indicator, while midpoint methodologies comprised ReCiPe, CML, TRACI, and Impact 2002+. However, these can belong to either category, depending on the application method. Figure 4 shows the linkage between Software, LCIA methodology and impact category. The thickness of the line corresponds to the frequency of use. SimaPro was the most common software overall, while ReCiPe was the most widely used LCIA method. In general, most of the impact categories were undefined.

Industrial WWT LCA papers commonly used ReCiPe (50%) and CML (33.3%) as the preferred impact assessment method, while urban WWT LCA studies applied ReCiPe (36.4%), CML (27.3%), and Eco-indicator (27.3%). Combination of methodologies included ReCiPe + USEtox (Broadhurst et al., 2015), ReCiPe (endpoint and midpoint) + IPCC (Masindi et al., 2018), in industrial WWT LCA, while Eco-indicator 95 + 99 (Roushdi et al., 2013), Eco-indicator + TRACI (Yami et al., 2015), in urban WT systems. ReCiPe was the most frequently used, which aligns with the ILCD handbook (European Union, 2010), and the recommendations of Corominas et al. (2020) but in contrary to other reviews (Byrne et al., 2017) in developed (Corominas et al., 2013a) and developing countries (Gallego-Schmid et al., 2019). Whereas the USEtox methodology feature in the LCA of industrial WWT represents the only study that accounted for emerging contaminants (e.g., micropollutants, microplastics, pathogens, antibiotic resistance) (Corominas et al., 2020). The prevailing LCIA method was dependent on the nature of the water being treated. However, the choice of midpoint or endpoint affects the results based on the disparities in the method of assigning environmental relevance to indicators (Corominas et al., 2020). Midpoint models offer a better degree of certainty; it is more precise for a LCA performed for a single system (Byrne et al., 2017). The endpoint models are mostly deemed more comprehensible to decision-makers since the outcome is synthesized into a single score. In contrast to midpoint models, for comparative LCAs, endpoint approaches that merge EIs into a single score can expedite environmentally informed decision-making (Byrne et al., 2017).

Ultimately, concerns about the influence of LCIA method on LCA outcomes exist (Ogbu et al., 2023). A study comparing LCIA methods found no substantial differences in GHG emissions, EP, and resources for WWTPs (Renou et al., 2008). Likewise, consistent outcomes were demonstrated for GWP, acidification and eutrophication for multiple LCIA methodologies (Eco-indicator 95&99, CML, EPS, and EDIP) (Simões et al., 2011). However, differences existed in the comparison of CML and e-Balance for evaluating WWTPs (Bai et al., 2017).

3.4.3.2 Impact indicators/categories

As obtainable in developing countries, GWP or Climate were considered by 92% of the included studies, as shown in Figure 4. Other common impact categories were acidification potential (80%), eutrophication (80%), and ecotoxicity (72%).

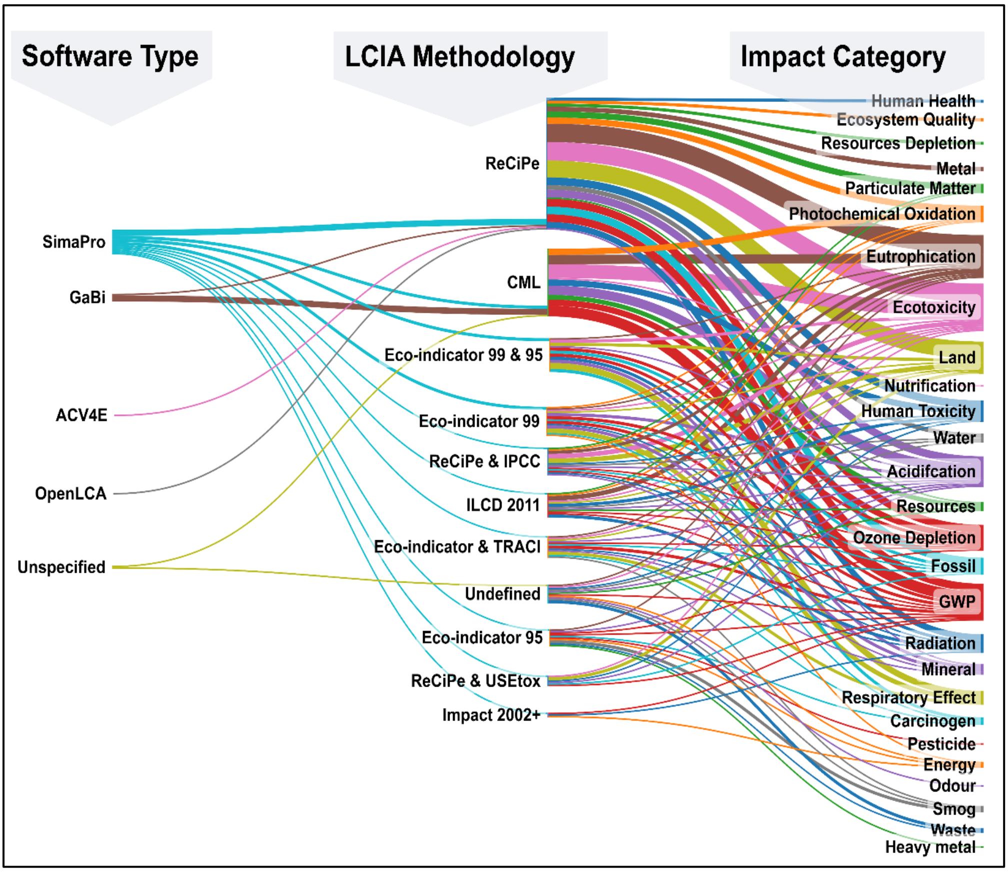

Figure 4. Sankey diagram of the linkage between Software, LCIA methodology and impact category/indicators in the reviewed studies.

These frequently occurring impact categories were established as key indicators for decision making regarding water systems (Corominas et al., 2020). Whereas GWP has political and social significance aligning with global climate change mitigation efforts. Ecotoxicity (terrestrial) plays an important role due to heavy metals and micropollutants content in sludge and effluent applied in agriculture (Corominas et al., 2013a). Ozone depletion potential was considered (52%) due to the concerns about the use of fossil fuels (Corominas et al., 2013a). Equally, acidification and photochemical oxidation formation connect specifically to other energy-sensitive impacts (Gallego-Schmid et al., 2019). Land use indicators were also common in studies assessing natural systems. These indicators are useful to minimise incorrect estimation of environmental benefits (Gallego-Schmid et al., 2019). Lastly, it's important to note that the emphasis on these impact categories may vary within Africa, depending on local environmental challenges, industrial activities, and WT technologies. Thus, EP and ecotoxicity are site-specific, while land use impacts are deemed substantially spatial- and temporal-sensitive (Gallego-Schmid et al., 2019).

Furthermore, contributional analysis from the selected studies showed that energy consumption from fossil fuels impacts GWP and human health, hence, significantly affecting the overall EI of WWT facilities (Friedrich et al., 2009; Goga et al., 2019). The contribution of GWP was often attributed to the intensity of energy consumption from fossil fuels (Broadhurst et al., 2015; Goga et al., 2019). GWP is a crucial impact category due to its global significance in mitigating climate change, which is a pressing global concern (Gallego-Schmid et al., 2019). Reducing GHG emissions from various processes, including WWT, is a significant contribution to global efforts to limit temperature rise (Gallego-Schmid et al., 2019). Ensuring that WWT processes do not harm public health is also crucial, as the release of pollutants can lead to diseases and health issues. The health and safety of populations are of utmost importance, making human health a key focus in environmental assessments (Corominas et al., 2020).

3.4.4 Interpretation

The interpretation phase combines the findings from the LCI and LCIA phases. This phase provides results consistent with the goal and scope definition to make conclusions, clarify limitations, and offer recommendations. It clarifies that the LCIA results show potential environmental consequences and not a forecast of definite impacts or limit exceedance (Finkbeiner et al., 2006). For WWT-related LCAs, this phase identifies the significant issues, such as the relative contribution of life cycle stages, for decision making (Corominas et al., 2020). The evaluation of completeness, sensitivity, consistency, and acknowledgement of limitations, as well as conclusions and recommendations, is done in this phase (Corominas et al., 2020). The common methods for uncertainty or sensitivity analyse were Monte Carlo (Pinelli et al., 2020), sensitivity analysis (Broadhurst et al., 2015; Rossi et al., 2019), and pedigree matrix (Anastasopoulou et al., 2018). The significant issues of concern were emissions, energy, and resource recovery. Limitations were considered in 76% of the papers and the key limitations were data (48%) (Anastasopoulou et al., 2018; Goga et al., 2019) and LCIA method (40%) (Bahi et al., 2020; Masindi et al., 2018). Literature comparison was applied in 88% of the papers (Mavhungu et al., 2021; Morsy et al., 2020).

Recognizing limitations in the interpretation phase of Life Cycle Assessment (LCA) is crucial. These limitations include data restrictions, technique shortcomings, and assumptions' vulnerabilities in the assessment (European Union, 2010). Transparent and clear LCA results are achieved by highlighting data gaps and uncertainties. Performing literature comparisons is also important to contextualize LCA results within previous research, ensuring harmony with current scientific understanding (Finkbeiner et al., 2006). These comparisons identify anomalies, patterns, or departures from known conclusions, enhancing the credibility of the assessment. Conducting uncertainty analysis is critical for determining the dependability of results (European Union, 2010). Sensitivity studies investigate potential outcome variations depending on input data, models, and assumptions, assisting stakeholders in determining confidence levels in the results (European Union, 2010). Preventing overinterpretation and ensuring relevant conclusions are crucial to the assessment's aims and scope (Corominas et al., 2020). Offering practical recommendations based on assessment findings promotes process improvements, regulatory changes, or more research, transforming LCA findings into real actions for stakeholders.

3.5. Global and Local Implications

The study extends beyond a local analysis to encompass global considerations and implications. These implications extend to a global scale, emphasizing the cross-disciplinary importance of the study. The limitations and challenges discussed are not unique to Africa but have relevance in many parts of the world. The findings of this study impact multiple facets and offer insights that can inform academic and professional stakeholders such as engineers, policymakers, regulatory agencies, and investors globally.

3.5.1 Implementation of LCA

LCA evaluates EIs and improves sustainability in WWT processes globally (Machado et al., 2007). It compares various methods and is crucial for improving the efficiency and sustainability of technologies (Buckley et al., 2011) in both developed and developing countries. LCA has limited study in Africa due to limited research (Karkour et al., 2021), but there has been growth in the WWT sector and LCA in developing countries (WHO and UNICEF, 2017), mainly focusing on decentralized treatment methods. Advanced WWT technologies and emerging pollution sources require more research (Gallego-Schmid et al., 2019). The application of LCA in water and WWT holds immense significance. It aids in informed decision-making and sustainable policy formulation by providing comprehensive insights into the environmental implications of various treatment options (Corominas et al., 2013b). Policymakers can use LCA to develop effective regulations and policies for new treatment projects. These assessments consider local conditions and available resources, ensuring that the environmental consequences of treatment methods are thoroughly evaluated before implementation.

LCA in W&WWT is critical for informed decision-making and sustainable policy formulation. It provides comprehensive insights into the EI of various treatment options (Byrne et al., 2017), enabling policymakers to develop effective regulations and policies for new projects. LCA identifies environmentally friendly and cost-effective treatment technologies, pinpoints resource hotspots, and minimizes waste production (Rashid et al., 2023). It is essential to integrate life cycle thinking into the engineering design process, considering the EI of technologies throughout their lifecycle. Investors and financial institutions should also use LCA to make more environmentally responsible investment decisions (Friedrich, 2002) by assessing the environmental implications of different treatment methods.

LCA studies (Masindi et al., 2018; Mavhungu et al., 2021) contribute to achieving SDGs 6 (clean water and sanitation) and 12 (responsible consumption and production), identifying environmentally friendly options and guiding sustainable water supply methods. Engaging stakeholders and sharing findings raises awareness, including professionals, academics, communities, and industry, can lead to identifying practical challenges, needs, and priorities. This emphasizes the importance of informed policy development driven by LCA insights for effective regulations and policies promoting responsible water use and sustainable treatment practices, with clear governance implications for policymakers.

3.5.2 Energy

Water and energy are indispensable resources for humans (Wakeel et al., 2016), and they are closely linked. Approximately 7% of global electricity is used for

WWT and providing potable water (Yang et al., 2010). Various factors influence energy usage in WWT, including water quality, technology, and geographical conditions (Wakeel et al., 2016), with the operational phase having the greatest impact. To optimize energy efficiency, policymakers are encouraged to promote the use of renewable energy sources in WT through incentives, subsidies, and renewable energy mandates. Regulations should also be introduced to enhance energy efficiency and encourage the adoption of energy-saving technologies, reducing carbon emissions and improving environmental performance.

This study highlights Africa's energy and financial constraints in W&WWT (Wang et al., 2014), where biomass is a significant contributor to the continent's energy consumption (Mukoro et al., 2021). However, energy consumption in treatment technologies needs to be reduced, leading to lower EI (Dong, 2012; Messaoud-Boureghda et al., 2012). Addressing these effects requires a dual approach: reducing energy consumption, improving treatment efficiency, and transitioning to cleaner, sustainable energy sources. Natural treatment technologies could be a more attractive alternative, but they may require more extensive land use.

This study emphasizes the significance of engineers in developing and implementing sustainable treatment technology designs. They should focus on minimizing EIs, optimizing treatment methods, and prioritizing energy efficiency in facility design. Financial institutions should support eco-friendly treatment technologies through project financing, promoting responsible investments. Adopting these technologies demonstrates an organization's environmental responsibility and commitment to reducing its ecological footprint.

Lastly, to promote sustainable treatment, policymakers should establish performance standards and incentives for environmentally friendly technologies. Regulatory bodies can set performance standards and offer incentives for greener solutions. Comprehensive wastewater management policies that prioritize sustainability and resource recovery should be developed. Integrating these efforts with SDGs can drive progress toward global targets. Policymakers should consider incorporating the study's findings into national or regional policies to address these SDGs effectively.

3.5.3 Resource management and economic implication

The significance of resource management and economic implications in WWT has been highlighted in this study. Water reclamation through WWT is crucial to both human health and the aquatic environment (Kamble et al., 2019). This study recognizes the challenges faced by developing economies, such as those in Africa, where investing in capital-intensive advanced WWT technologies is often impractical (Andersson et al., 2016; Ngeno et al., 2022). Innovative approaches to WWT, such as the valorisation of available waste as flocculants and adsorbents in treatment facilities, are advocated. Notably, agro-industrial by-products like biochar and carbon nanotubes.

Furthermore, this study highlights the importance of engineering cost-effective, resource-efficient, and environmentally sustainable W&WWT treatment systems in regions with limited resources. These systems should involve the local community in the design process, optimize designs for minimal operating costs and maintenance requirements such as low-tech or nature-based solutions. This study also stresses the economic opportunities of resource recovery in wastewater and its potential to create job opportunities and benefit agriculture, aligning with the social and economic aspects of the sustainability framework. Reusing wastewater in urban agriculture as both a water source and a nutrient is identified as a valuable practice. The Goreangab water reclamation project in Africa is a successful resource recovery and reuse initiative, which recycles potable water from municipal sewage (Andersson et al., 2016).

Resource management practices and engineering solutions should be tailored to specific regional needs, and policymakers should allocate funding for sustainable treatment technologies. Financial institutions should invest in these projects, aligning with circular economy principles, and regulations should standardize responsible resource recovery with quality standards for by-products. Regulatory bodies should set principles that support and standardize resource recovery practices in WWT, including quality standards for the sale of by-products like biogas and organic fertilizers, ensuring compliance with environmental and health regulations.

Consequently, there exists a conflict between the demand and supply of land resource for WWTPs and constraint in the available land resources is fast becoming a bottleneck (He et al., 2018). Consumption of water because of human activities has increased at a rate of growth twice as fast as the population growth rate. It is further estimated that by 2030, demand for water will increase by 283% (Andersson et al., 2016). Hence, the resulting increased energy demand has led to higher GHG emissions and increased land use changes (Muscat et al., 2020). Therefore, this has resulted in an increase in the cost of land rent. Hence, sustainable land use practices are crucial to address these challenges.

3.5.4 Study Limitations

The study's limitations are examined here, including the potential for missing valuable studies during the article screening process. This was mitigated by supplementary search and perusing review papers and the selected articles' reference lists. The literature search can be improved with ontology schema for a more robust process. Additionally, involving multiple stakeholders in the article screening process can reduce the likelihood of overlooking relevant studies. Despite the limited number of studies selected, this review represents the current reality of LCAs in the water sector in Africa, as demonstrated in other studies (Karkour et al., 2021; Maepa et al., 2017). The limited geographical and temporal representation in the studies can impact the applicability of the findings, particularly in the context of WT in Africa. This might lead to a potential selection bias and affect the representativeness of the findings. Moreover, this study stems from a larger project that commenced at the end of 2020 with scoping and a literature review. At the time of reference collection, screening, and full-text review, it was challenging to access articles published after 2020 due to the time-bound nature of projects. We acknowledge the importance of considering recent literature for a comprehensive review. However, the temporal characteristics, including time and location, are reported for transparency as recommended by the STARR method (Zumsteg et al., 2012) for reviewing LCAs, as evident in other reviews (Gallego-Schmid et al., 2019; Lam et al., 2020). Regrettably, the development and preparation of the manuscript required a significant amount of time before it was ready for submission. Nevertheless, a quantitative component of the literature review (Ogbu et al., 2023) stemming from our broader project was successfully published earlier.

Future reviews should aim to incorporate a broader spectrum of studies, potentially involving more databases or engaging experts in the field to identify additional relevant research. This can result in more representative findings. Moreover, ignoring grey literature might have led to a bias toward published studies, potentially missing critical perspectives and findings. A good archive includes unpublished reports, technical papers, theses, and dissertations. Future studies can mitigate this by actively searching and including grey literature. Additionally, the absence of stakeholder engagement could mean that the present studies might have missed some real-world insights, practical challenges, needs, or priorities of stakeholders involved in water and wastewater management in Africa. Future research should involve stakeholders through interviews, surveys, or focus groups to capture their perspectives and ensure that the findings align more closely with the needs of the industry and community.

3.5.5 Challenges and Future Directions

A significant hurdle in the practical application of LCAs in W&WWT is the limitation of available data. Many studies in Africa and developing regions rely heavily on European data (Karkour et al., 2021), introducing uncertainty in local applications. There are LCA databases developed exclusively for Africa (Mukoro et al., 2021), but available data is limited (Karkour et al., 2021). One strategy in addressing this challenge involves creating more locally led comprehensive LCA databases projects that combine data from both Africa and beyond. This enhances accessibility and reliability. Focus on local principal investigator led data collection to bridge the gap between European-derived data and the African context. Regional emission models and characterisation factors are key components of this section. These components are influenced by energy sources used in treatment plants, transportation of materials, and waste disposal methods, local water usage, and ecosystem, which differ by geographical location.

It's essential to encourage interdisciplinary collaboration among scientists, engineers, economists, and policymakers for holistic solutions. Include stakeholder perspectives through local community engagement to identify practical challenges and priorities. Cross-continental collaboration should be promoted to share best practices, data, and expertise in LCA, fostering a global knowledge exchange. Investigating the impact of using LCA results in educating the public and stakeholders about the environmental consequences of their actions through awareness campaigns, which can promote responsible water use and sustainable treatment practices.

The water-energy nexus poses challenges. Also, the interplay between energy and chemicals in treatment processes and the rising energy demand needed for high-quality effluent, especially in Africa, increases emissions. There is a lack of geographical and temporal representative data in most LCA studies. Data on energy use in the water sector are limited (Macharia et al., 2020). Collaboration among researchers, policymakers, and practitioners for a cleaner, sustainable energy transition is crucial. Extensive research should focus on identifying and developing energy-efficient technologies and practices, including innovative treatment methods, energy recovery systems, and the integration of renewable energy sources. Investigating the feasibility and impact of integrating renewable energy sources, e.g., solar, wind, and hydropower, is necessary to improve energy efficiency and reduce GHG emissions.

Expanding research into novel approaches for resource recovery and reuse in WWT is essential for human health and environmental preservation. Investigating the broader economic implications of resource recovery and reuse, especially in the context of job creation and its impact on agriculture, is vital. Analysing the economic viability of W&WWT projects and studying successful case studies, for lessons that can be applied in other regions, is crucial. The growing demand for land resources in WWT poses a growing challenge. Exploring innovative approaches to maximize land use efficiency in treatment processes is essential. Further exploration of natural treatment technologies as more energy-efficient alternatives is vital. Investigating different natural treatment methods, their EI, and finding ways to overcome land use challenges associated with their implementation is fundamental.

3.6 Conclusion

The review provides a comprehensive assessment of the state of LCA in Africa's water sector, shedding light on the associated environmental impacts and highlighting critical gaps and opportunities. The review underscores the dominance of South Africa and Egypt, with absence of countries like Nigeria. However, the studies reveal valuable insights into the operation of treatment technologies, particularly in urban wastewater management amid ongoing urbanization and population growth across Africa.

The findings highlight a critical need for technological advancements and data infrastructure enhancements in Africa's water sector. Practitioners are more focused on the impacts of the operational stage of treatment technologies and performance optimization. The reliance on fossil fuels for electricity generation emerges as a significant contributor to adverse impacts, emphasizing the urgency for transitioning to renewable energy. The prevalence of incomplete data, particularly regarding sludge characterization and local emission factors, questions the integrity of studies and impedes robust research. Bridging these gaps entails encouraging comparative assessments, technology transfer, and fostering collaboration among stakeholders to narrow the disparity between Africa and developed regions.

However, the absence of stakeholder engagement in this analysis and the limited scope of selected studies may pose potential limitations in capturing real-world insights and applicability. Nevertheless, the review underscores the vital role of LCA in informing sustainable decision-making and policy formulation in WWT, advocating for interdisciplinary collaboration to address challenges, and incorporating local perspectives to enhance study reliability and applicability. Recommendations include the development of tailored LCA databases and methodologies, integrating regional emission and characterisation factor models, and enhancing stakeholder participation to ensure holistic sustainability in WWT practices in Africa.

Moreover, resource recovery and reuse in WWT promises economic and environmental benefits imperative for sustainable water management in Africa and beyond. By integrating LCA insights into policy formulation, encouraging stakeholder engagement, and establishing performance standards for eco-friendly solutions, policymakers can drive tangible progress towards a more sustainable and resilient water future for all. Moving forward, embracing innovative approaches and prioritizing sustainable solutions, Africa can progress towards achieving the SDGs related to clean water and sanitation, responsible consumption and production, and climate action.

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4. Estimating the Ecological Performance of Water and Wastewater Treatment in Africa: A meta-analysis

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Abstract

This article is the result of a systematic review of published LCA studies on water and wastewater treatment in Africa. After applying the search and selection criteria, 32 observations for energy use were included and 20 for the global warming potential (GWP) and the eutrophication potential (EP). The dependent variables were categorized by technical, method, and typology factors. The meta-regression model aligned with the descriptive statistics on the variation of the dependent variables due to water source but not location. Regarding energy use, GWP, and EP, the water source and the study location had the most significant influence in contrast to the life cycle impact assessment (LCIA) method. There is a need for more such LCA studies in Central and Western parts of Africa.

Keywords

Carbon Footprint; Energy Use; Environmental Impact Assessment; Greenhouse Gases Emissions; Sludge.

4.1 Introduction

The most significant increases in pollutant exposure are expected in low- and lower-middle-income countries, mainly due to population expansion and economic growth [1] and insufficient water and sanitation systems [2], especially in Africa. The UN Sustainable development goals bordering on water scarcity, waste avoidance, reasonable consumption and production, and sustainable cities have been attracting attention in recent times. Water and sanitation play a critical role in this goal as it merges into several value chains from waste generation to disposal. It also presents an opportunity to recover water resources [3–5]. Due to rapid population expansion, poor economic conditions, and lack of water and sanitation infrastructure, Africa is projected to have peak pollutant exposure. African countries have water quality and effluent discharge regulations, which are rarely met. However, meeting these requirements involves using certain chemicals, resources, and energy, which has a detrimental effect on the environment. Water treatment facilities are classified as high-energy consumers [1, 2]. Thus, energy production is often of concern since it is mainly generated from fossil fuels. The production of electricity is one of the leading contributors to environmental pollution [6].

Furthermore, during the life cycle (LC) of water treatment facilities, pollutants are generated from the production and use of chemicals, biological treatment processes, discharge of effluent and sludge, and haulage of chemicals, fuels, and sludge. Life cycle assessment (LCA) practitioners documented that global warming potential (GWP), eutrophication potential (EP), and ecotoxicity potential (ETP) are the critical environmental impact indicators associated with water treatment [7]. These documents demonstrate discrepancies among studies associated with water treatment-related LCA. These discrepancies could be categorized into technical, methodological, and typological factors. Technical factors include influent and effluent characteristics, energy use, treatment technique, and plant location. Methodological factors include the LCA approach, the impact assessment methodology, the impact indicators, and the uncertainty analysis. However, typological concerns include the publication year, the location of the author(s), and funding sources. Therefore, there is a gap in providing a summary estimate of the environmental characteristics of water treatment facilities in Africa. Also, more is desired from existing knowledge to understand how these factors impact the outcome of water treatment-related LCA studies [3, 4, 7].

Besides, the application of meta-analysis has been demonstrated in different disciplines to collate, combine, and synthesize data to reach a robust estimate nearer to reality. In wastewater treatment (WWT), meta-analysis was used to characterize energy use and environmental impacts of wastewater treatment plants (WWTPs) [6]. It was also applied to appraise antimicrobial systems [8], the removal efficiency of organic pollutants [9], categorize chemicals in activated sludge [10], model fate and transport in surface water [11, 12]. More precisely, meta-analysis has been used to synthesize LCA studies [6, 11–13]. To the best of the authors' knowledge, only one study [6] attempted to use meta-analysis statistical methods to perform a quantitative analysis of the environmental profile of water treatment-related LCA studies. However, the study only considered the disparities in energy use and environmental impacts (EIs) with certain technical variables; no attention was paid to the methodological or typological aspects. The present paper considers the three families of variables. In addition, it employs a similar approach to synthesize the energy use and environmental impacts of water treatment in published case studies in Africa.

Hence, the objective of this study is to (i) quantify and characterize energy use, and environmental impacts of water treatment in Africa, (ii) verify how the results of water treatment-related LCAs in Africa differ with certain factors, and (iii) identify the key drivers of variation if any.

4.2 Materials and Methods

4.2.1 Selection of relevant articles

The systematic review checklist of the developed Standardized Technique for Assessing and Reporting Reviews based on the Preferred Reporting Items for Systematic reviews and Meta-Analyses statement protocol was used to ensure accuracy. The Web of Science, Scopus, and Google Scholar were the sources of articles in this review. Thoroughly fashioned strings of keywords were used to search for papers available up to December 2021 linked to the theme of this review. Details of keywords are given in supporting information (Sect. S1). These searches were matched with dates from the year 2000. Also, the reference lists of included articles were examined to find other studies related to the topic of the present review. Current reviews of LCA studies in Africa and those related to water treatment were also checked for additional studies [3–5, 14–17]. The theme of the present study is to analyze the peculiarities of energy use and EIs of water treatment processes in Africa using existing LCA studies. Thus, the articles selected for such analysis should be closely connected to the theme. Only independent research articles other than overviews were included in this study. Articles included in this study should at least consider the treatment among other processes in the entire lifecycle. The studies that evaluated other processes (such as collection, conveyance, reuse, and discharge) without considering the treatment step were excluded. For the present study, water treatment refers to both raw water purification and wastewater treatment. The LCA methodology specified by ISO 14040 [18] for environmental assessment was adopted in all selected articles.

Also, studies incorporated into this analysis considered at least one of energy use, GWP and EP in forms (digits, with units) that are extractible and not only in pictures and charts. Lastly, since the functional unit (FU) forms a basis for quantifying material flow in LCA, studies excluded were those without FU in m^3 or those convertible to this format. Finally, 36 case studies (as shown in Figure 1) were selected for this review because the main objective was LCAs for water treatment located within the African continent. A previous study by Li et al. [6] has detailed explanations of these selection criteria. Furthermore, all statistical analyses were completed using the meta [19] or metaphor [20] packages in R software [21]. Details of data analysis are shown in Supporting Information (Sect. S1).

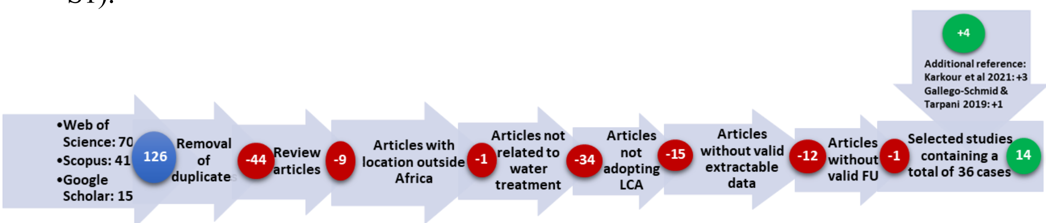

Figure 1. Process of article screening for establishing the relevant LCA studies for water treatment.

4.3 Results and Discussion

The results are first described based on location and water source. Then, meta-regression analysis results are presented.

4.3.1 Description of data

Consequently, after applying the search and selection criteria, 36 observations were covered. Energy use was considered in 32 out of 36. A list of the selected articles is presented in the Supporting Information (Sect. S4.). GWP was evaluated in 20, and EP in 20. South Africa's long history of LCA research is evident, while Egypt dominates the number of observations. Among the selected cases, 43% were conducted in Egypt, 38% in South Africa, 11% in Cameroon, and 5% in Morocco. Figure 2 shows the summary of the energy use and EIs from the selected studies. Municipal WW treatment was assessed in 62% of the selected studies, while 19% assessed raw water and industrial WW treatment each. Most of the studies considered only the operational phase of the life cycle of the treatment plants; only 35% included the entire life cycle from construction to demolition. Among the studies that specified their primary LCIA method, 33% adopted the

CML method, while ReCiPe and Eco-indicator were used in 27% and 24%, respectively. Most studies employed the SimaPro software; about 21% did not specify.

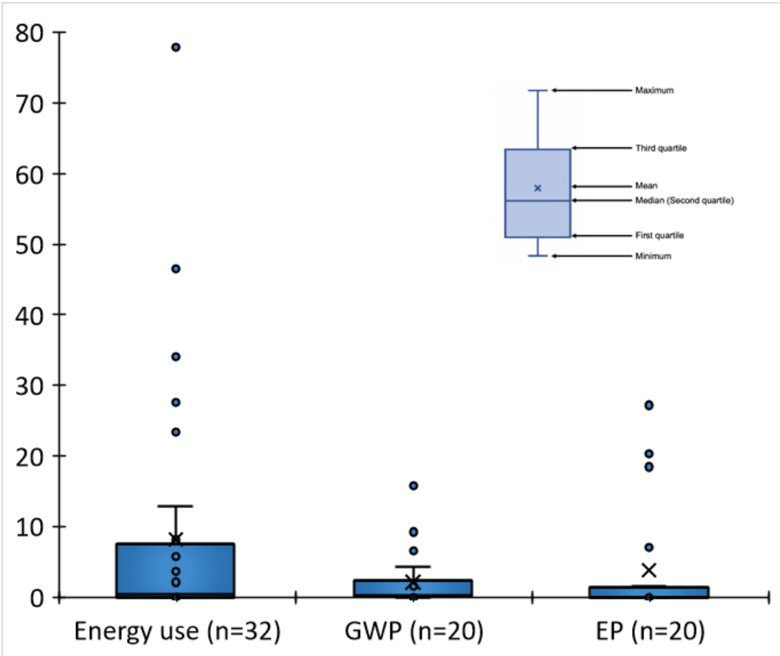

Figure 2. Summary statistics of energy use and impact categories for water treatment studies. Energy expressed in kWh m^{-3}, GWP in kg CO_2-eq m^{-3}, EP in 10^{-2} kg PO_4^{3-}-eq m^{-3}, n = number of observations.

Moreover, the cumulative number of studies (CNS) published rose abruptly from 2009, as shown in Figure 3. This trend aligns with those of LCA in the African water sector, as depicted in a recent review [16] of all LCAs in Africa. Likewise, there was a considerable change in the water metric data within this timeframe. There was a corresponding sudden increase in values of total water withdrawals (TW), average water stress (AWS), and average water use efficiency (AWE), while average withdrawal per capita (AWC) decreased [22].

Around 2011, some countries in northern Africa were already water-stressed, relying entirely on water recycling and reuse due to the over-extraction of renewable freshwater deposits [23]. Similarly, the decrease in withdrawals per capita perhaps shows that the dwindling water resources were insufficient for the growing populace. Thus, there could have been an awareness of the impending danger and the severe environmental consequences of water scarcity. Therefore, resources and research were allocated to the water sector in Africa. The water use efficiency also improved significantly, an all-time high in over a decade.

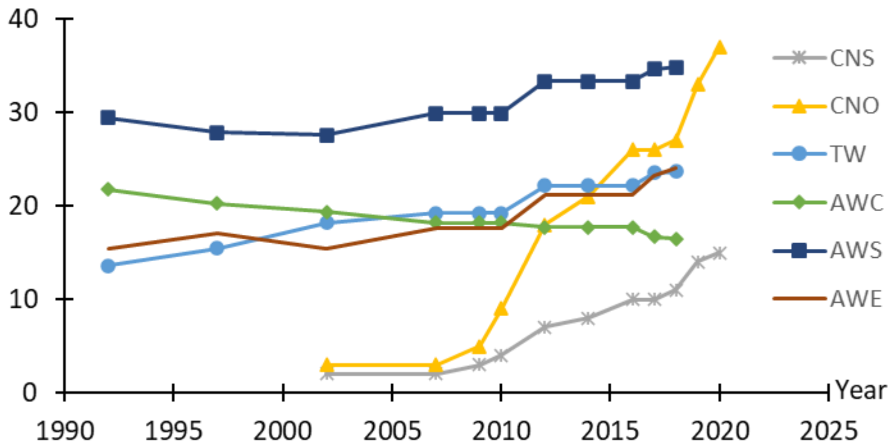

Figure 3. Cumulative number of studies and observations per publication year; and FAO water metrics. CNS - Cumulative nos. of studies; CNO - Cumulative nos. of observations; TW - Total withdrawal (10^{10} m^{-3} yr^{-1}); AWC - Average Withdrawal per capita (x 10 m^{-3} yr^{-1} per inhabitant); AWS - Average Water stress (%); AWE - Average Water use efficiency (USD m^{-3}).

4.3.2 Description of results

Statistical analysis of 36 case studies indicates that for EIs, the GWP vary from 1.69 x 10^{-14} to 15.9 kg CO_2-eq m^{-3}, and EP range from 1.3 x 10^{-15} to 0.27 kg PO_4^{3-} -eq m^{-3}. In comparison, the energy use stretches from 0.001 to 77.87 kWh m^{-3}. The energy use and environmental impact categories for various locations are shown in Figure 4. The general analysis showed that the energy consumption and environmental impacts varied significantly owing to certain factors. Complete statistical description of energy use, GWP and EP with the associated variable families is presented in Supporting Information (Tab. S2). The detailed calculation of the pooled mean by location and water source is shown in Supporting Information (Figure S1 – S12). Subsequently, a detailed analysis of the influence of these significant factors was demonstrated.

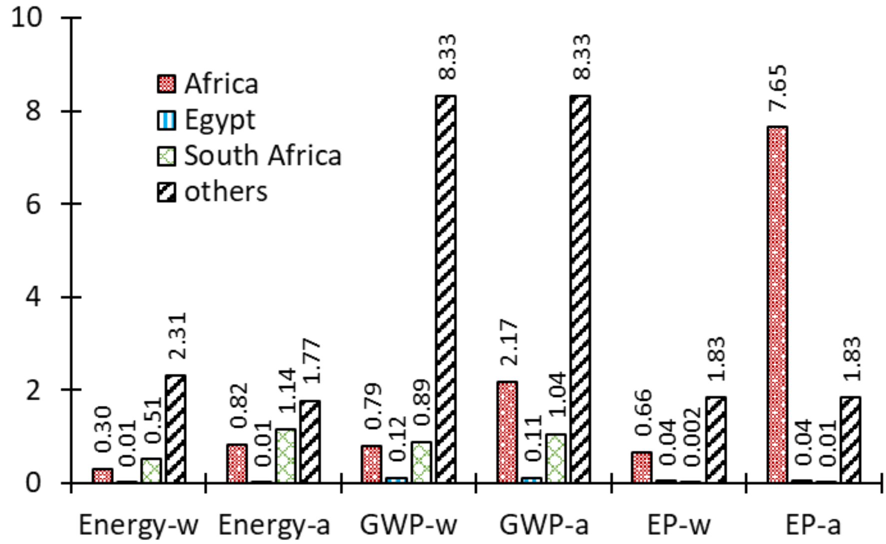

Figure 4. Summary estimates for energy use and EIs of observations by geographical location expressed as pooled (-w) and arithmetic (-a) means. Energy (x 10^1 kWh m^{-3}), GWP (kg CO_2-eq m^{-3}), EP (x 10^{-1} kg PO_4^{3-}-eq m^{-3}). Others = Africa less Egypt and South Africa.

4.3.2.1 Geographical location

The mean values of energy use and EIs vary substantially between locations. There is an uneven representation of countries in the available data: South Africa and Egypt have about 84% of the total estimates. Regarding energy use, GWP, and EP, South Africa occupied 39%, 45%, and 45%, while Egypt had 31%, 20%, and 20% of the estimates, respectively. South Africa had higher values for energy use than Egypt and the overall mean.

South Africa also had higher GWP values than Egypt and the overall mean. However, other countries (excluding Egypt) had the highest value. Regarding EP, Egypt and South Africa had the lowest values compared to the overall mean and other countries. These disparities have been linked to population characteristics, living conditions, economic advancement [6], climate change (e.g., ambient temperature), statutory discharge standards, electricity rates, and geo-morphological attributes (e.g., elevation, altitude). Including the industrial outlook [24], electricity mix [25], technology and scale, policy and governance issues, and incidents when incentives in the sector are absent or deceitful [26].

South Africa is classified as a chronic water-scarce nation and embraces water reuse to mitigate drought [27]. Consequently, in this review, most studies in south Africa utilized different variations and combinations of energy-intensive technologies; ion exchange and softening [28], reverse osmosis, ultrafiltration [28, 29], membrane filtration [30], eutectic freeze crystallization, evaporative crystallization [31], and magnesite-lime & ash-CO_2 bubbling [32] for treatment. Another energy-consuming heating method for treatment was studied in Uganda. According to AQUASTAT [22], South Africa has 923 treatment facilities (the highest number in Africa) and a treatment capacity of 2.414 x 10^9 m^3 yr^{-1}. (second largest in Africa). The increased development of treatment facilities and awareness of the environmental impacts of different technologies, in general, is demonstrated by the Environmental Performance Index (EPI; specifies performance pointers that show how nations of the world manage environmental problems). South Africa ranks top for wastewater treatment, waste management, and combating climate change in Africa. These also consume energy, nevertheless. Hence, ongoing optimization of energy in WWTPs in South Africa demonstrate that 71% of the treatment facilities in South Africa can generate power with a possibility of 20-50% energy savings [27, 33]. In contrast, less energy-consuming technologies: natural and aerated lagoons in Morocco [34], rapid sand filtration [35], and filtration, wetlands [36], activated sludge [37] in Egypt were also utilized.

Moreover, energy-intensive technology for water treatment has also been studied worldwide, comparable to the apparently high average in Africa. Again, these variations are attributed to the quality, volume, and legal treatment levels at various locations [38]. Studies from China and USA have shown that desalination technologies using thermal and membrane processes are the most energy intensive. Such as reverse osmosis (RO): 2.4-8.5 kWh m^{-3}, vapor compression: 8-15.85 kWh m^{-3}, multistage flash distillation: 26.42-68.69 kWh m^{-3}, multiple-effect distillation: 39.71-105.7 kWh m^{-3}, nanofiltration and electrodialysis [39, 40]. Furthermore, energy use intensity for RO and other energy-intense technologies varied globally, Eritrea 2.33 kWh m^{-3}, Kuwait 4.52 kWh m^{-3}, Caribbean Island 3.15 kWh m^{-3} [41], South Africa 3.97-4.39 kWh m^{-3} [29], China 6.282 kWh $m^{-3}$and Saudi Arabia 4.4 kWh m^{-3} [42]. On the other hand, dilapidated and ageing technology and unscientific management of the wastewater industry in China was reported as critical issue for high energy intensity and subsequent emission of pollutants [6], which can also apply to facilities in Africa. Likewise, studies have shown that energy use intensity varies with location, maybe due to the prevalence of a particular treatment technology. WWTPs in Canada and France had high energy consumption compared to the USA, Spain, Germany, and Italy [26].

Besides, regions with higher water risks, dependence on groundwater or desalination sources, and those that use tertiary treatment for their WWT have relatively higher energy intensities [43].

In the present study, electricity generation and use were reported as the chief contributors to environmental impacts. It can be attributed to the electricity mix dependency on fossil fuels, e.g., coal, oil, gas, etc. Moreover, high energy use, especially fossil fuels, produces high emissions of hydrocarbons and NO_2 [6, 25]. Hence, most observations that reported electricity generation and use had electricity mix from coal [28, 44] or fossil fuel [29, 32, 45]. Consequently, the impact category with the most influence was GWP for most of these studies. Oil, gas, and coal constitute 39, 30, and 21% of energy consumption in Africa, respectively. And 8, 40, and 28%, respectively, for electricity production. Subsequently, they contribute 36, 22, and 34 %, respectively, to CO_2 emissions from fuel sources in Africa. South Africa and Morocco are vital contributors to CO_2 emissions from coal, while Egypt, Algeria and Nigeria contribute the most to emissions from oil and gas [46]. Likewise, regarding total GHG emissions, significant contributors were DRC Congo, South Africa, Nigeria, Egypt, and Algeria [47]. A similar trend is observed in the present study, as the GWP of facilities from South Africa is higher than those from Egypt. Equally, the indirect GHG emissions from treatment facilities arise mainly from energy consumption during aeration, pumping, wastewater, and sludge transportation. And contribute 14-68% to the whole carbon footprint [48]. GWP is linked to N_2O, CH_4, and CO_2 emissions from Nitrogen, BOD, and COD [7]. GHG emissions for WWTPs also demonstrated inconsistency from USA 0.00-0.56, China 0.13-0.90, and South Africa 0.07-1.22 kg CO_2eq m^{-3} [25]. Several studies have shown a proportional relationship between energy use and GHG emission intensity [26, 43].

EP relates to various Nitrogen, Carbon, and Phosphorus species, such as BOD, TKN, NH_4, NO_3, NO_2, PO_4^{3-}, TSS, and TP. It is a function of the concentration of pollutants in the effluent, regional environmental considerations [49], weather conditions, and seasons [50]. But most common LCIA methods fail to integrate these local differences, particularly in developing countries [4]. Furthermore, since eutrophication partly depends on the concentration of nutrients in emissions to water, untreated wastewater likely has a higher EP than treated effluents. Moreso, there is a reported insufficiency in the capacity of sanitation systems and wastewater treatment facilities in Africa. Between 2008-2019, the total volume of municipal WW generated (x 10^9 m^3) was 77.3, 32.2, 7.6, 5.6, 3.3, 3.1, and 1.3 in Egypt, South Africa, Morocco, Libya, Tunisia, Ghana, and Senegal, respectively [22]. Figure 5 shows the proportions of treated, untreated, and direct use of untreated municipal WW for irrigation purposes in Africa compared to other countries.

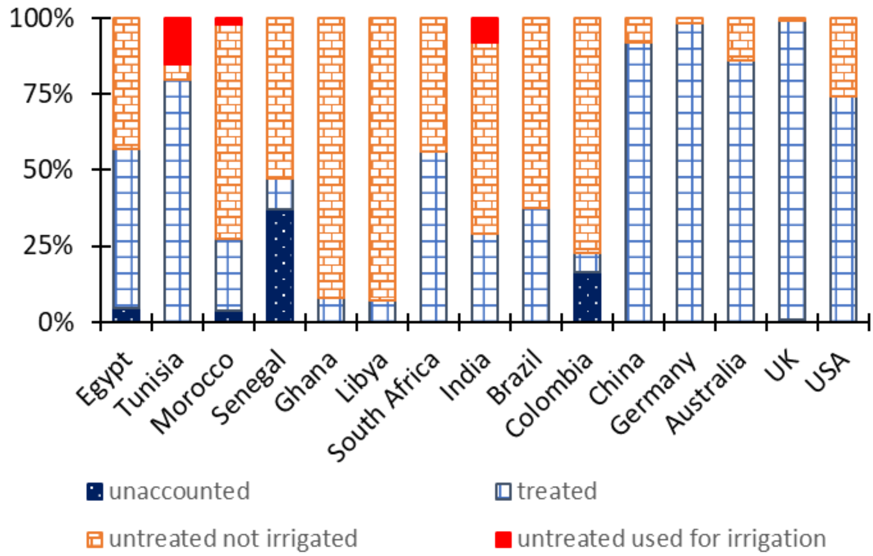

Figure 5. Characteristics of municipal wastewater in several countries. Unaccounted equals produced wastewater less the treated and untreated fractions.

The ratio of untreated WW discharged into the environment is higher in most African countries, hence a higher chance of eutrophication. From treatment facilities in Africa, the discharge standard is less stringent, and the level of compliance is low compared to developing countries, which is indicated by the EP values. Likewise, variations exist in the effluent discharge standards of developing countries. Nigeria has a BOD (mgO_2/L) limit of 30-50, Tanzania 30 and 50 for Ghana, Uganda, and Malaysia, respectively. For DS (mg/L), Thailand and Tanzania had as high as 3000 and low as 200 in Nigeria. Other parameters, such as COD and SS, showed wide discrepancies [51]. These inconsistencies in **parameters reflect in the discharges and, consequently, EP values.**

4.3.2.2 Water source

The mean values of energy use and EIs in the treatment of raw water and wastewater are displayed in Figure 6. As mentioned earlier, only -a mean values are commented on. The treatment of raw water consumed more energy than wastewater. When disintegrated, industrial consumes more energy than municipal WW treatment. Like the variations observed in various locations, energy consumption in the water sector varies due to groundwater characteristics, climate, seasonal temperature, rainfall, water requirement, volume of water and treatment technologies [40]. Furthermore, the discharge standard and treatment scale are responsible for a significant disparity in energy use outcomes and EIs intensities [6].

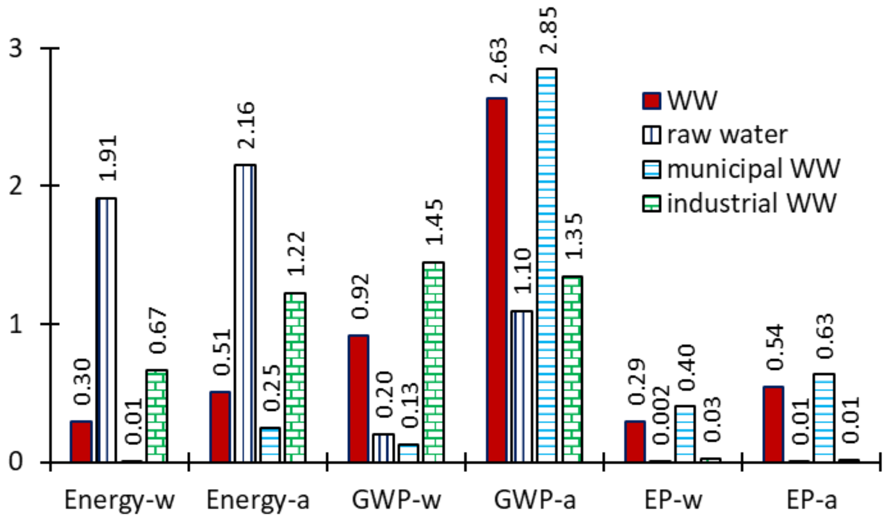

Figure 6. Summary estimates for energy use and EIs of observations by the source of treated water as pooled (-w) and arithmetic (-a) means. Energy (x 10^1 kWh m^{-3}), GWP (kg CO_2-eq m^{-3}), EP (x 10^{-1} kg PO_4^{3-}-eq/m^{-3}).

The flow rate, the equivalent population, the dilution factor and the plant layout influence the intensity of energy use [26]. Meanwhile, most of the observations under raw water and industrial WW were the treatment of water with high total dissolved salts. Such as industrial WW from mine drains [29, 31, 32], seawater [29] and saline water [28]. Raw water treatment is energy intensive; yet desalination systems consume more. However, the energy use values in this review fall within the range of different desalination technologies listed earlier, up to 105.7 kWh m^{-3} [40].

In general, the critical source of energy consumption in water or wastewater treatment is the nature of the pollutant to be removed. Before supply, potable water is purified to strict physiochemical standards devoid of pathogens, which might not necessarily apply to effluent discharge [42]. Although raw water might not contain as many pollutants as wastewater, the degree of purification needed to treat raw water to potable standards is higher. Subsequently, raw water of saline origin consumes more energy and resources. Similarly, industrial WW often contains recalcitrant pollutants such as heavy metals and phenolic compounds, which often require advanced technologies for their removal [52]. Raw water treatment, depending on the source, consumes more energy than wastewater. On average, municipal water treatment spends 0.2-8.5 kWh m^{-3} in Australia and 0.07-5.47 kWh m^{-3} in California. For recycled water treatment, 2.8-3.8 kWh m^{-3} in Australia, 0.33-3.1 kWh m^{-3} in California, while wastewater consumes 0.44-1.1 kWh m^{-3} in Australia and 0.38 to 1.22 kWh m^{-3} in California [42]. Similarly, industrial WW consumes more energy than municipal WW treatment [25]. Thus, as observed in the present study, potable water production consumes more energy than municipal and industrial WW treatment, respectively.

Generally, in centralized WWT systems, with certain exceptions, the energy use intensity is inversely proportional to the increase in the capacity [6], [26]. This is attributed to more stable and automated operational conditions, the use of efficient equipment, and a more experienced workforce at larger facilities [26]. On the other hand, systems using cycle activated sludge systems (CASS) processes consume more energy than anaerobic/anoxic/oxic (AAO) and anoxic/oxic (AO), respectively. But there is less energy use during the construction and demolition stages of AO and CASS systems. However, CASS has complex operational procedures, such as aeration with high energy consumption [6]. Similarly, membrane reactor (MBR) has the highest energy use compared to biological nutrient removal (BNR) and conventional activated sludge (CAS) systems. Due to the energy requirement of aeration units and losses due to fouling and clogging [26]. Regarding sludge management, aerobic stabilization uses more energy than anaerobic digestion but depends on plant size and pollutant removal efficiency. Dewatering and mechanical centrifugation also take a high chunk of the energy demand of treatment facilities [26].

Meanwhile, the treatment technologies, sludge handling and disposal methods influence GWP and EP values [5, 48]. Water and sludge treatment processes are accountable for the direct GHG emissions from treatment facilities. They contribute 23-83% to the overall carbon footprint while 1-13% come from offsite sludge disposal [48]. Likewise, the direct emission profile of treatment systems depends on influent characteristics, dissolved Oxygen, and water temperature [6]. This indicates why WWT can have higher GWP than raw water because wastewater has a high load of biomass (BOD, COD), thus, higher direct emissions of CH_4 and N_2O species. And likewise, the superior energy use intensity of raw water amounts to greater indirect emissions from energy consumption. Also, the GWP like energy use intensity decreases with expanding the scale of treatment

[25]. The GWP of AAO systems is higher than CASS and AO because of their higher energy use intensity [6].

Furthermore, though criticized for high CH_4 emissions, anaerobic technologies have lower GHG emissions than other technologies. Upflow anaerobic sludge blanket (USAB) configurations, when compared to modified Ludzak-Ettinger (MLE) and Bardenpho, showed higher direct but lower overall GHG emissions. This is mainly because anaerobic technologies are more energy efficient and allow for energy recovery. The energy recovery offsets the total emissions [48]. Similarly, sludge drying contributes 22-59% to total GHG emissions, while anaerobic digestion of sludge reduces it by about 12-38%. However, landfill sludge disposal has higher GHG emissions than incineration, composting, and agricultural use [48].

EP for sanitation systems were at the peak for SBR than biofilters, soil infiltration, and dry toilet systems. This was associated with nutrient concentration and discharge pattern [50]. CASS and AAO processes are supposed to be more efficient than AO, which reflects that AO has the highest EP intensity. With increasing capacity, the nature and concentration of pollutants lessen. Thus, EP can increase with sudden expansion due to the diminishing efficiency of treatment processes [6]. However, decentralized (source-separation) systems had higher EP than centralized [5]. Recycling sludge as a Phosphorus product has a higher EP than digested sludge. EP can be reduced using decentralized recovery systems, optimization of chemical use in sludge management, accounting for ammonia emissions and avoided fertilizers [5].

4.3.3 Meta-Regression results

To further elucidate the homogeneity in the pooled variables, meta-regression is used to identify the influential factors. It also identifies the moderating effect of these factors with the corresponding magnitude and direction. The outcome of the meta-regression analysis is shown in Tab. 1. The results obtained for energy use, GWP, and EP are presented in Tab. 1. All regression results are presented in the reduced form. Under the energy (same for GWP, EP) column, the estimate and standard error results from the ordinary least square (OLS) HCCM procedure are shown. Only coefficient estimates significant at p-value <= 0.1 have been included in the reduced form. This explains the empty cells in Tab. 1. Concerning the model information, N represents the number of observations. The R-squared indicates the variation percentage defined by the model. The adjusted R-squared statistic (Adj. R-squared) is like the R-squared, but the former is insensitive to the number of variables contained in a model. Also reported are the logarithm likelihood (Log-likelihood), Fisher test statistic (F-stat.), Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) for the model.

In this section, comments on the results are only centered on the signs and significance level of parameter estimates since the absolute magnitude is trivial [13]. The consequences of factors influencing the estimates of energy use and EIs are subsequently argued by pertinent literature comparison. Again, the purpose of the meta-regression is to test if the variables affect the values of energy use and EIs from primary LCA studies.

In the regression models, energy use has an adj. R-squared of 63% and the F-stat p-value significant at 1%, indicating a significant joint impact on energy use by the variables considered. Likewise, a significant combined effect on EP was shown at an F-stat p-value of 1% with adj. R-squared 68%. However, the regression model for GWP is insignificant, but some variables separately influence GWP, as indicated in Table 1.

For the sources of water, the estimates indicate a statistically lower energy use for municipal WW treatment than for industrial WW (p-value <0.01). While raw water treatment expends more than industrial and municipal WW (p-value <0.001). Compared to municipal WW treatment, the energy use is statistically lower for municipal by 60 kWh $m^{-3}$and higher for raw water treatment by 1.5 kWh m^{-3}. At the same time, GWP and EP are higher (p-value <= 0.01) for municipal WW treatment. GWP and EP are statistically higher for municipal by 1.42 kg CO_2-eq m^{-3} and 0.001 kg PO_4^{3-}-eq $m^{-3,}$ respectively. Hence, these suggest that the source of water treated has an influence on energy use and EI results. This aligns with the visuals in and the arguments for Figure 6. The treatment technology, influent characteristics, and effluent requirements were critical contributors to this as explained earlier.

Similarly, South Africa has a negative influence on energy use for the geographical locations, significant at 1% level. Thus, energy use is significantly lower for South African studies than in Egypt. The estimates indicate treatment processes in South Africa consume about 75.77 kWh m^{-3} less than in Egypt. But the visual from descriptive statistics in Figure 4 opposes this trend. It is unexpected because both the arithmetic and pooled means showed that energy use in South Africa is higher than in Egypt.

Table 1. Meta-regression results for energy use, GWP, and EP.

	Energy ($kWh\ m^{-3}$)		GWP ($kg\ CO_2\text{-eq}\ m^{-3}$)		EP ($kg\ PO_4^{3-}\text{-eq}\ m^{-3}$)	
Model	**estimate**	**std. error**	**estimate**	**std. error**	**estimate**	**std. error**
Intercept	59***	19.11	401.090***	0.072	0.43***	0.003
Technical						
source						
industrial WW (ref)						
municipal WW	-59.58***	18.13	1.420***	2.12E-12	0.001***	4.26E-14
raw water	1.53***	7.6E-13				
Geo. Location						
Egypt (ref)						
South Africa	-75.77***	3.49	3.120***	0.072	-0.006*	0.003
others			9.378***	2.574	0.184***	0.036
Study Methodology						
life cycle stage						
C/O (ref)						
C/O/D	-1.18***	0.05	-1.657***	0.037	-0.002***	6.05E-06
O			-5.206***	0.052	-0.006***	1.06E-05

Significant codes: 0 '***' 0.01 '**' 0.05 '*' 0.1

Table 1. Meta-regression results for energy use, GWP, and EP contd.

	Energy (kWh m^{-3})		GWP (kg CO_2-eq m^{-3})		EP (kg PO_4^{3-}-eq m^{-3})	
Model	**estimate**	**std. error**	**estimate**	**std. error**	**estimate**	**std. error**
LCIA method						
CML (ref)						
Eco-indicator						
ReCiPe						
others						
software						
GaBi (ref)						
SimaPro			5.938***	2.6E-12	0.006***	8.14E-12
others			5.037***	0.072		
Study Typology						
Year of publication			-0.202***	2.91E-11	-2.12E-04***	5.31E-15
Model Information						
N	32		20		20	
R-Squared	0.77		0.67		0.83	
Adj. R-Squared	0.63		0.36		0.68	
Log-likelihood	-111.83		-45.06		40.15	
F-stat. (p-value)	5.39(0.0006)		2.2(0.117)		5.5(0.0068)	
AIC	251.66		112.125		-58.29	
BIC	272.18		123.078		-47.35	

Significant codes: 0 '***' 0.01 '**' 0.05 '*' 0.1

Nevertheless, GWP values from Egypt are lower than those from South Africa and other countries. While EP values are lower in South Africa (p-value <0.1) compared to Egypt and other countries ($p<0.01$) respectively. Compared to Egypt, GWP values are higher in South Africa and other countries by 3 and 9 kg CO_2-eq m^{-3}, respectively. While EP values are lower in South Africa by 0.006 kg PO_4^{3-}-eq m^{-3} and higher by 0.2 kg PO_4^{3-}-eq m^{-3} in other countries than Egypt. Hence, the geographical location influences energy use and EIs results. Most of these discrepancies were attributed to energy/electricity mix, electricity rates, demography, economic and industry outlook, and the geo-morphology of countries.

For stages considered, the studies reporting only the complete life cycle (C/O/D) of the treatment facilities had significantly lower (p-value <0.001) energy use values compared to those considering construction and operation phases only. However, emission estimates were lower in studies reporting O and C/O/D than C/O stage by 5 and 2 kg CO_2-eq m^{-3} for GWP and by 0.006 and 0.002 kg PO_4^{3-}-eq m^{-3} for EP. Moreover, a meta-analysis study [6] ignored the effects of these boundaries in the analysis. Meanwhile, the construction phase contributes more than 5% [7] and up to 50% [53] to the overall environmental impact of non-intensive technologies and large plants, respectively. Thus, the present study has gone further to elaborate the variations due to the boundaries considered.

In contrast, the LCIA method showed no significant impact on energy use outcomes and EIs in the primary studies considered. The comparison of LCIA methods in assessing WWTPs showed no significant variation in GHG emissions, EP, and resources [54]. Likewise, a study on virgin and recycled plastic found consistent results for GWP, acidification and eutrophication for five LCIA methods (Eco-indicator 95&99, CML, EPS, and EDIP) [55]. However, there was inconsistency in the comparison between CML and e-Balance for assessing WWTPs [56]. Expectedly, the choice of modelling software and LCIA method had no significant influence on energy use. This could be predicted since the energy use values are debatably not primary outcomes of LCA studies. Although it could be argued that software also contains inbuilt databases like the Ecoinvent, where data on energy use for a unit process can be obtained for LCA studies. Nevertheless, the influence seems insignificant. Regardless, the GWP values from other software (excluding SimaPro) are significantly higher (p-value <0.01) than from GaBi. Whereas EP values from SimaPro are substantially higher (p-value <0.01) than from GaBi. Hence, the choice of software influences the GWP and EP outcomes.

Lastly, publication year has a significantly negative (p-value <0.01) on GWP and EP values, respectively. The estimates imply a decrease in GWP by 0.2 kg CO_2-eq m^{-3} and EP by 0.0002 kg PO_4^{3-}-eq m^{-3} per annum. Hence, the publication year affects outcomes of GWP and EP. The reason for this might not be apparent but is not unconnected to the rising awareness of sustainability and various steps being put in place over the years to reduce the environmental impacts of the water sector. However, several studies, as seen in Sect. 3.2.1. and 3.2.2., showed that energy use is directly proportional to GWP but does not apply in this instance. This could be due to the lack of energy and resource recovery scenarios in the observations in the present study. Only two studies reported energy recovery via biogas [37, 45]. However, biosolids and organic manure were also recovered [35, 36, 45, 57, 58].

4.4 Conclusion

The water and sanitation infrastructure cannot meet the needs of the rapidly growing African population. Most countries are water-stressed and employ alternative sources of water reclamation to meet their water needs. However, the environmental implications of these infrastructures are of great concern. LCA has been used to assess the environmental impacts of treatment facilities. It has also shown that energy and resource recovery and proper accounting can help offset these environmental impacts. The present study used a meta-analytic approach to summarize the energy use, GWP, and EP intensities of water treatment. It also systematically corroborated the influential factors on the LCA studies. The results of this study are expected to provide an extensive synopsis and improve comprehension of key variables that induce variations in energy consumption and emissions. The following conclusions can be deduced from the present study:

i. The results indicate an energy use intensity order: energy use intensity of industrial wastewater treatment is statistically higher than municipal wastewater. However, raw water treatment towards potable water production has a significantly higher energy intensity. Furthermore, despite the nature of the water treated, the intensity of energy use was statistically different between all study locations. Water scarcity and salinity contributed to this incident. Based on the significance level of the regression model, the water source, geographical location, and the life cycle stage are critical drivers of variation in intensity of energy use.

ii. Furthermore, GWP suggests a substantial correlation with the intensity of energy use, as shown in other studies. The higher the intensity of energy use, the higher the GWP. However, the GWP values were lower for raw water than for wastewater treatment. GWP was lower for Egypt than in

South Africa, but the overall average was much higher. The regression model indicated a separate but not joint influence of variables on GWP. The software model, water source, life cycle stage, and publication year are the most influential. But the location also had an influence.

iii. Additionally, EP estimates are higher for municipal wastewater treatment than industrial wastewater and raw water. South Africa has lower EP values than Egypt and the overall average. Similarly, the regression model indicates that the key drivers of variation in EP values are life cycle stage, water source, modelling software, and publication year. The geographical location also contributed.

Nonetheless, as with all meta-analyses, there are limitations to the present study. Firstly, acquiring and screening articles for data extraction might have bypassed some valuable studies. However, some supplementary search was done by examining review papers on LCA related to water and wastewater treatment or Africa. The literature search can be improved using ontology schema to link databases for a more robust process. Next, a comprehensive correlation and regression would have been possible if the selected studies reported all three variables. However, not all selected studies reported values for energy use, GWP and EP. For example, some articles reported on energy use but not GWP and EP. Therefore, the study could not analyze any statistical relationship between the dependent variables. Additionally, an ideal analysis would compare the total life cycle from the construction of the treatment facility to its operation and demolition. However, less than 30% of the observations assessed the entire life cycle. Moreover, the selection process included studies that evaluated at least the treatment process. Those that did not consider the treatment process were eliminated. However, some studies assessed collection, conveyance, treatment, and disposal. Thus, these two scenarios of system boundary might have introduced some degree of bias. Hence, the trends may differ if all studies, especially those that considered the treatment process, included the numerical values of energy use and EIs with consistent units. Furthermore, future research can analyze estimates for each of the three predominant stages of the life cycle. Furthermore, this study may not have fully identified all variables in the families: technical, methodological, and typological variables that affect LCA outcomes in studies of water and wastewater treatment. Lastly, one of the most significant limitations is that most studies are inconsistent with units, especially in reporting the functional units. The conversion to cubic meters might have introduced some errors.

Supporting Information

Supporting Information for this article can be found under DOI: https://doi.org/10.1002/ceat.202200562. This section includes an additional reference to primary literature relevant for this research [59]. See Appendix A

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Conflict of interest

The authors declare no conflict of interest.

Symbols

Abbreviations

AAO	Anaerobic/anoxic/oxic
AO	Anoxic/oxic
AWE	Average water use efficiency
AWC	Average withdrawal per capita
AWS	Average water stress
BNR	Biological nutrient removal
BOD	Biochemical oxygen demand
C/O	Construction/operation stages
C/O/D	Construction/operation/demolition stages
CAS	Conventional activated sludge
CASS	Cycle activated sludge systems
CML	Centrum voor Millikunde Leiden
CNO	Cumulative number of observations
CNS	Cumulative number of studies
CO_2-eq	Carbon dioxide equivalent

COD	Chemical oxygen demand
DS	Dissolved solid
EDIP	Environmental Development of Industrial Products
EIs	Environmental impacts
EP	Eutrophication potential
EPS	Environmental Priority Strategies
ETP	Ecotoxicity potential
FU	Functional unit
GHG	Greenhouse gases
GWP	Global warming potential
HCCM	White's Heteroskedastic Consistent Covariance Matrix
LCA	Life cycle assessment
LCIA	Life cycle impact assessment
MBR	Membrane reactor
MLE	Modified Ludzak-Ettinger
O	Operation stage
OLS	Ordinary least square
RO	Reverse Osmosis
RW	Raw water
SBR	Sequencing batch reactor
SS	Soluble solid
TKN	Total Kjeldahl Nitrogen
TP	Total Phosphorus
TSS	Total suspended solids
TW	Total withdrawal

UASB	Upflow anaerobic sludge blanket
WW	Wastewater
WWT	Wastewater treatment
WWTPs	Wastewater treatment plants

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5. Techno-economic Analysis of Electricity Generation from Household Sewage Sludge in Different Regions of Nigeria

Adopted from: Ogbu, C.A., Alexiou Ivanova, T., Ewemoje, T.A., Okolie, C.O. & Roubik, H. (2023). Techno-economic analysis of electricity generation from household sewage sludge in different regions of Nigeria. Science of The Total Environment (IF: 9.8), 166554. https://doi.org/10.1016/j.scitotenv.2023.166554

Abstract

Waste management has been a chronic environmental challenge in Nigeria, coupled with declining economic performance due to energy crises. This study was designed to estimate electricity potential of sewage sludge to meet the 2030 Renewable Energy target. However, there was a need to fill the gap in data related to wastewater management in Nigeria. The wastewater and sludge generated from households were evaluated based on data on population, access to water, and coverage of sewer networks. Consequently, the technical and economic feasibility of electricity generation was assessed using Anaerobic Digestion (AD) and Incineration (INC) scenarios. The core results found that North Central had the highest potential for wastewater generation (142.8-403.6 billion litres/yr) and collection (8.3-37.5 billion litres/yr) over 20 years. However, the South East had the highest average sewer collection rate of 9.08%. The AD technology was the most technically viable, with a maximum generation of 6.8 GWh/yr in the North Central. In comparison, the INC outperformed AD in most of the financial viability indicators considered viz-a-viz: Life Cycle Cost (LCC), Net Present Value (NPV), Pay Back Period (PBP), Internal Rate of Return (IRR), Levelized Cost of Energy (LCOE). The AD had a higher NPV of 16.3-69.58 million USD and a shorter PBP of about 4 years. The INC had a lower LCC of 0.1-0.34 million USD, LCOE of 0.046-0.094 USD/kWh, and a higher IRR of 19.3-25%. Additionally, the sensitivity of NPV and INC to changes in economic factors would be noteworthy for investors and policymakers. Ultimately, the choice of technology should reflect the fiscal goal and priorities of a project.

Keywords: Waste-to-energy, biogas, financial feasibility, energy cost, sustainability, wastewater.

Abbreviations

ACS, Annualised Cost of System; AD, Anaerobic Digestion; C, Carbon; CHP, Combined Heat and Power; FCT, Federal Capital Territory; H, Hydrogen; HHV, Higher Heating Value; INC, Incineration; IRR, Internal Rate of Return; LCC, Life Cycle Cost; l/c/d, litres/capita/day; LCOE, Levelized Cost of Energy; LFG, Landfill Gas; LFGTE, Landfill-gas-to-Energy; LHV, Lower Heating Value; MSW, Municipal Solid Waste; N, Nitrogen; NC, North Central; NE, North East; NESP, National Environmental Sanitation Policy; NPV, Net Present Value; NW, North West; O, Oxygen; O&M, Operation and Maintenance; OFMSW, Organic Fraction of Municipal Solid Waste; PBP, Payback Period; PI, Profitability Index; REMP, Renewable Energy Master Plan; S, Sulphur; SDG, Sustainable Development Goals; SE, South East; SS, South South; SWS, Sewage Sludge; SW, South West; UAE, United Arab Emirates; USD, United States Dollar; WASHNORM, Water, Sanitation and Hygiene National Routine Mapping; WtE, Waste-to-energy, WW, Wastewater; WW Col., Wastewater collection; WW Gen., Wastewater Generation; WWTP, Wastewater Treatment Plant; WWTPs, Wastewater Treatment Plants.

5.1 Introduction

The poor treatment of wastewater (WW) in developing countries has led to the proliferation of diseases. The Sustainable Development Goal (SDG) 6 targets reducing the amount of untreated WW released into the environment. Developing countries often do not meet WW discharge standards, which continues to be a significant environmental concern (World Bank, 2021). Similarly, Nigeria's primary public health concern is poor access to safe potable water and sanitation. In 2019, approximately 80 million people had no access to secure hygiene facilities. Furthermore, 29% of households in rural areas engage in open defecation. As a result, substantial volumes of WW are released into the environment, untreated or undertreated (World Bank, 2021).

The main problems existing Wastewater Treatment Plants (WWTPs) face in developing countries include irregular power supply and mismanagement of sludge. Likewise, there are limited information on wastewater and faecal sludge production, treatment, and disposal in Nigeria (World Bank Group, 2017). Moreover, sludge has been previously classified as sewer and non-sewer sludge. Sewer sludge is made up of sludges from sewerage and WWTPs. On the contrary, non-sewer sludge is faecal sludge from a septic tank or pit latrine (Englund & Strande, 2019). Faecal sludge disposal techniques in Nigeria include treatment at designated treatment plants, burial in covered or open pits, and discharge into water bodies (FMWR et al., 2022; World Bank Group, 2018). In one case, the sludge is dried on site as feedstock for AD or a medical incinerator (World Bank Group, 2018). The management of sludge at WWTPs could be similar as there is very limited information, in addition to the fact that most plants are not operating optimally. However, an operational facility in Nigeria is equipped with drying beds for the drying of sludge. Most dried sludge accumulates within the facility, some being used as manure (Saidu et al., 2019). Other WWTPs also practice agricultural application and landfilling of sewage sludge (Nikolopoulou et al., 2023). Additionally, a recent study (Ogwueleka et al., 2021) also investigated the disposal of wastewater treatment plant sludge by bio-drying technique to produce a material usable as fuel in steam and power generators (Navaee-Ardeh et al., 2010).

Furthermore, Nigeria's economy depends on energy, but most of the population lacks access to electricity (Ziady, 2021). Oil and gas remain the mainstay of power in Nigeria; however, the high intensity of Nigeria's energy implies an ineffective energy utilisation (Ritchie et al., 2022). The Nigerian government launched a plan to increase the amount of renewable energy in the energy mix from 13% in 2015 to 36% by 2030. The Renewable Energy Master Plan (REMP) was intended to promote energy security and regulate the carbon footprint of the country's energy sector (ITA, 2021). The progression of the energy situation has left more to be desired, marked by erratic supply, an outdated grid, and infrastructure.

Waste-to-energy (WtE) technologies have received attention as a means of renewable energy generation. Significant studies have been conducted to quantify and characterise Municipal Solid Waste (MSW) in Nigeria: thus, demonstrating the potential energy recovery options of MSW. Several studies examined the potential of MSW energy recovery in Nigerian cities. Incineration (INC), Anaerobic Digestion (AD), and Landfill-Gas-To-Energy (LFGTE) have been studied for WtE in Lagos and Abuja. The AD had the highest energy generation (Lagos (683 kWh/t) and Abuja (667 kWh/t)) (Nubi et al., 2022). Selected landfills in Adamawa state received 15 Gg/yr of MSW and released 0.31 Gg/yr of LFG with a methane content of 82.95 Mg. A projected 33.78 GWh of heat or 10.14 GWh of electricity can be generated from these landfills (Usman, 2022). In Ibadan, methane production from AD and LFGTE technologies averaged 104.66-212.15 x 10^6 m^3/yr and 22.65-127.65 x 10^6 m^3/yr for a 20-year period, respectively. The mean generation of electricity during this period was 321.73-652.15 GWh for AD and 63.25-436.18 GWh for LGTE (Ayodele et al., 2018). The treatment of abattoir waste in Ile-Ife, Southwest Nigeria, by AD, showed the potential to generate 1,040 MWh of electricity at a conversion efficiency of 0.25. The waste was digested using a 2-batch reactor for 30 days, producing biogas at a mean rate of 1.03 l/day with a methane content of more than 63% (Odekanle et al., 2020). The Organic Fraction of MSW (OFMSW) in selected Nigerian cities generated 491 Gg of methane, which is 3.48×10^9 kWh of electricity from 26,600 Gg of waste in 2015. It is projected to increase to 4.74×10^9 kWh electricity due to 669 Gg of methane from 36,250 Gg of waste in 2030. With an estimated income of USD 365.04×10^6 and USD 473.82×10^6 for 2015 and 2030, respectively (Yusuf et al., 2019). Using a university campus as a model community through the WtE calorific value technique, the energy recovery potential of MSW was approximated to be 2,490 kWh/d of electricity (Okeniyi et al., 2012). In addition, the Swedish WtE model was used to simulate the generation of electricity from MSW. The model showed a combustible 14 million tonnes of waste in Nigeria worth about 4.4 TWh of electricity (Akhator et al., 2016). Also, waste generation in 2020 was estimated at 40 million tons based on a population of 158 million and a waste generation rate of 0.5 kg/person/day. The forecast showed that with a calorific value of 9.6 MJ/kg, there is the potential to generate 3,000 MW of electricity (Atta et al., 2016). However, the characterisation of the MSW components showed that 73% was organic with an energy content of 13,022 KJ/kg. Methane generation over 10 years was estimated at 27,517 tonnes

(Akintayo and Olonisakin, 2014). Other studies evaluated the potential for biogas from OFMSW (Ngumah et al., 2013), energy from biomass sources (Ojolo et al., 2012), fuelling steam generators using MSW (Adeoti et al., 2014), comparative analysis of hybrid WtE systems (Ogunjuyigbe et al., 2017), and electricity generation from LFGTE technology (CPE, 2010).

Furthermore, the low heating value and high moisture content of sewage sludge significantly impact its use in electricity generation through AD and INC. However, biomass material with a calorific value of 6.25 MJ/kg (EPA, 2013) or 6 MJ/kg (World Bank, 1999) can be used for bioenergy. The calorific value of sewage sludge in various studies attests to its suitability as an energy source. In the analysis of sewage sludge as an energy feedstock in Italy, the moisture content ranged from 71.8-79% of total weight with a Higher Heating Value (HHV) of 12.7-15.5 MJ/kg dried basis (Bianchini et al., 2015). In France, the ultimate analysis showed C 58.5%, H 9%, N 5%, O 27.45%, and S 0.05% with HHV of 20.43 MJ/kg (at 6.2% moisture content) while proximate analysis revealed moisture 6.2%, ash 16%, volatile matter 58.9%, and fixed carbon 19% (Jayaraman and Gökalp, 2015). Moisture, ash, volatile matter, and fixed carbon content in Canada were 73.21, 4.02, 22.52 and 0.26%, respectively. C, H, N, S and O were obtained as 13.2, 9.8, 1.2, 0.5 and 71%, respectively, for the wet sludge with HHV of 5.65 MJ/kg and 18.75 MJ/kg after microwave drying (Chen et al., 2014). A comparative analysis of coal, agricultural biomass (wood and oat), and sewage sludge showed an HHV of 23.5, 17.6, 17.2, and 12.8 MJ/kg, respectively. Sewage sludge had an ash content of 33% and a higher N content (4.1%) than wood <0.05%, oat 1.7%, and coal 2.2% (Magdziarz and Wilk, 2013). Moreover, due to increased organic and volatile content, the primary sludge has a higher energy content than the secondary. The calorific value of the dry matter of the secondary sludge of different treatment technologies was found to be in the 13.5-18.5 MJ/kg range. The digested sewage sludge had a comparatively lower calorific value of 8.5-10 MJ/kg (dry basis). Ultimately, the calorific value of sewage sludge ranges between 8-21 MJ/kg (Singh et al., 2020). At the same time, the quantity of sludge generated during WW treatment varies from 1-6% of WW. The Lower Heating Value (LHV) of sludge is influenced by its dry matter content and the organic content of the dry matter. 4.2% of the initial dry matter content is obtained after the dewatering and drying of the raw sludge. The LHV of dried sludge ranges from 9-12 GJ/ton (at 90% dry matter content) (Ozcan et al., 2015).

Unlike in Nigeria, several WtE plants worldwide are fuelled by sewage sludge (Ijoma et al., 2022). Predominant technologies for WtE from sewage sludge include AD, INC, pyrolysis, gasification, and fuel cells. Some run solely on sewage sludge; for example, an alternative electricity source in Dubai runs on domestic sewage generating 45,000 MWh/yr electricity and is worth around 89 million USD (Meladi, 2019). Another plant worth 4 million USD in Sofia produces 2.4 MWh/yr electricity (powering plant operations) (Ijoma et al., 2022). A 29.4 million USD plant in Serbia generates 3.8 MWh/yr of electricity for optimal operations and heating (MET Group, 2021). Similarly, two biogas plants in Oregon, USA, generate 6,000 MWh/yr and 4,324 MWh/yr for electricity and heating purposes (Clackamas County, 2018; Hayward, 2018; Loggan, 2021). In South Africa, a Biogas-Combined Heat and Power (CHP) plant generated 725 GWh of electricity and 1,150 GWh of heat per annum from organic solid waste and slaughterhouse WW (Russo and von Blottnitz, 2017). Additionally, an innovative nano-membrane toilet design for a Bill and Melinda Gates Foundation project had a capacity of 4,620 kWh per 16.2 kg of human faeces and urine (Anastasopoulou et al., 2018). At a Wastewater Treatment Plant (WWTP) in Gamasa, Egypt, an integrated biogas plant produces about 1,396.5 kWh of electricity to supplement the power needs of the WWTP (Awad et al., 2019). Meanwhile, other plants mix sewage sludge with biomass waste. Such as in South Africa (cattle manure & OFMSW) and Finland (WWTP sludge plus OFMSW), with a capacity of 4.4 MWh/yr and 40 GWh/yr, respectively (Bailey, 2021; Ijoma et al., 2022). Several sanitation systems combined with one or more AD, CHP and INC technologies were studied in Uganda. The systems were fuelled by cow dung, food waste, and domestic sewage and had a capacity of 441.3-826 kWh/day of electricity and 740.2-1385.5 kWh/day of heat (Agunyo et al., 2019). Nevertheless, the potential of energy recovery from sewage has not received attention in Nigeria, and little or no information is available.

In addition, data on the volume and distribution of WW in Nigeria seem to be a mirage. However, some attempts have been made to estimate the volume of WW generated, collected, and treated in Nigeria. In most conventional databases, such as AQUASTAT (FAO, 2021), data on WW metrics in Nigeria are absent. On the one hand, limited data until 2020 is available from the Joint Monitoring Programme (JMP) (WHO and UNICEF, 2021) database and a UN (UN-Habitat and WHO, 2021) report. The available JMP data is non-volumetric, population-based, and at the national level, although segregated into rural and urban residence types. The JMP data is also segregated according to facility type, service type, service level, and management element. However, the UN data is volumetric but only national level estimates. On the other hand, a study (Jones et al., 2021) used a data-driven model to aggregate, assess, and homogenise country-level WW data from electronic databases while using regression to predict unattainable data. Another study (Ijoma et al., 2022) estimated the generation of sludge from domestic WW using data on domestic freshwater withdrawal at the country level from the World Bank repository. Nevertheless, these studies arguably applied top-to-bottom approaches based on national-level data. The peculiarities and variations in different micro-locations (e.g., cities in the country), such as sanitation type, water accessibility per capita, and population, were not considered simultaneously.

Therefore, the objectives of the study are: (i) to estimate the volume of household WW generation and collection through sewer networks for different geo-political regions in Nigeria, (ii) to estimate the generation of Sewage Sludge (SWS) for the regions, and (iii) to provide a holistic assessment of the technical and economic potential of two different WtE technologies (i.e., INC and AD) for electricity generation in the regions.

5.2 Methodology

5.2.1 Area under study and data collection

In this study, the energy generation potential of the produced SWS is determined using the most recent population statistics of the National Bureau of Statistics (NBS, 2023) and projected for 2022-2042 based on a growth rate and per capita access to water in the 36 states and the Federal Capital Territory (FCT) of Nigeria. The growth rate per state and FCT is published by (NBS, 2023), while water accessibility (l/c/d) was obtained from the WASHNORM report (FMWR et al., 2022).

In theory, domestic WW contains WW from households and selected services (UN-Habitat and WHO, 2021). Like the UN report (UN-Habitat and WHO, 2021), the information and estimates in the present study cover only WW generated by households. Therefore, subsequent parts of this paper may mention household WW instead of domestic WW and vice versa. The WW generation was estimated as a percentage of the per capita water accessible at each location. The portion of WW collection was adapted as the percentage of coverage of the sewer network or households connected to a central sewer network at each location (FMWR et al., 2022). The model to estimate the amount of sewage sludge processed from AD and INC was adopted from previous studies (Nubi et al., 2022; Ogunjuyigbe et al., 2017). Nigeria comprises 36 states and the FCT, subdivided into six geo-political zones, as shown in Figure 1.

The North East (NE) zone comprises Adamawa, Bauchi, Borno, Gombe, Taraba, and Yobe states. The North Central (NC) zone contains Benue, Kogi, Kwara, Nasarawa, Niger, Plateau states, and FCT Abuja. The North West (NW) zone includes Jigawa, Kaduna, Kano, Katsina, Kebbi, Sokoto, and Zamfara states. The

South East (SE) zone comprises Abia, Anambra, Ebonyi, Enugu, and Imo states. South South (SS) includes Akwa Ibom, Bayelsa, Cross River, Delta, Edo, and Rivers states. Finally, the South West (SW) zone comprises Ekiti, Lagos, Ogun, Ondo, Osun, and Oyo states.

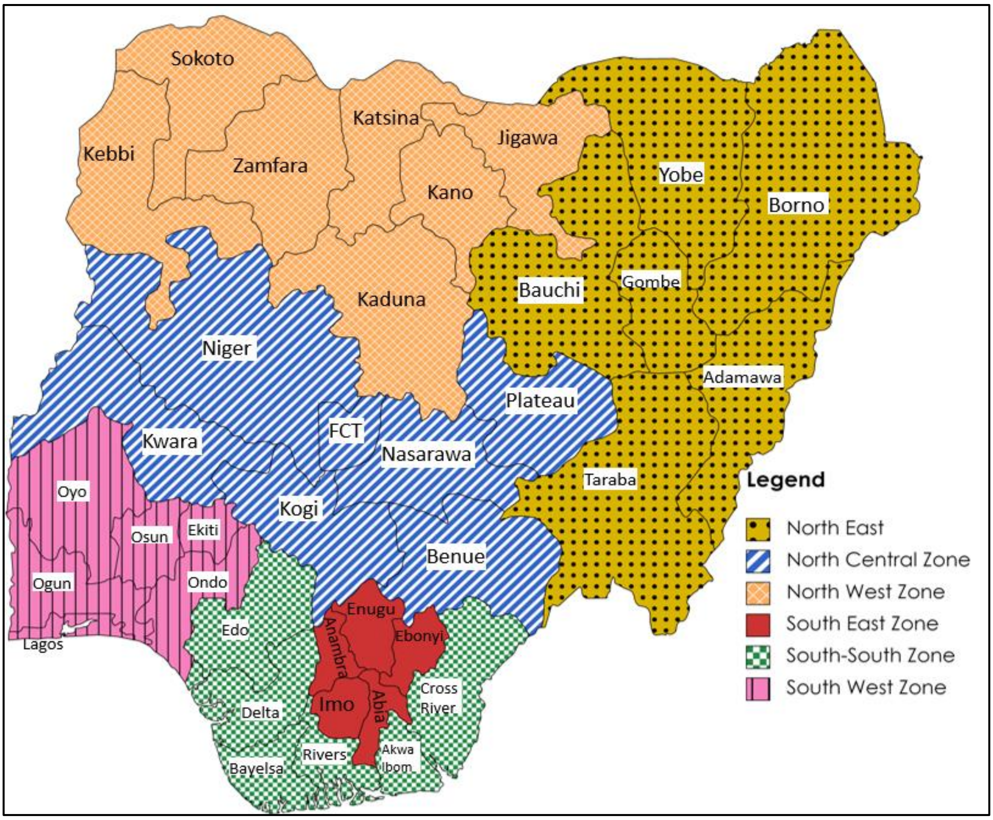

Figure 1 The map of Nigeria showing the different zones and states under them.

5.2.1.2 Estimation of sewage sludge for potential energy generation

The WW generation is estimated to be 90% of the water available to a person per day (V_{WA}) (Ijoma et al., 2022). V_{WA} in each state is obtained from the WASHNORM report (FMWR et al., 2022). The WW generation (litres) per capita per day can be calculated as:

$$V_{WG} = 0.9 \times V_{WA} \quad (1)$$

The total volume of WW (litres) generated per year is given as:

$$V_{WGT} = P \times V_{WG} \times 365 \quad (2)$$

$$P = P_0(1 + r)^t \quad (3)$$

where P is the projected population of each location based on a growth rate, r; 365 = the number of days per year; P_0 denotes the 2006 census population, which serves as the base; t = the extrapolated time of interest.

The annual WW collection in litres is given as:

$$V_{WCT} = P \times V_{WG} \times WW_{CR} \times 365 \quad (4)$$

where WW_{CR} = wastewater collection rate, adapted from the percentage of households connected to a central sewer network (FMWR et al., 2022).

5.2.2 Energy recovery techniques for scenarios based on technology

5.2.2.1 Anaerobic digestion technology for energy recovery from sewage sludge

The theoretical potential volume (m^3/t) of biogas production from the AD of organic matter is determined using the Buswell equation (Amoo and Fagbenle, 2013; Ogunjuyigbe et al., 2017):

$$C_nH_aO_bN_c + (n - 0.25a - 0.5b + 0.75c)H_2O \rightarrow (0.5n - 0.125a + 0.25b + 0.375c)CO_2 + (0.5n + 0.125a - 0.25b - 0.375c)CH_4 + cNH_3 \ (5)$$

The values of the variables n, a, b, and c are determined by normalised mole ratio (Ogunjuyigbe et al., 2017) given as:

$$Mole\ Ratio = \frac{K[C,H,O,N]}{M[C,H,O,N]} \quad (6)$$

where K is the elemental composition (C, H, O, N) derived from the ultimate analysis of sewage sludge (Singh et al., 2020); M = molar mass of the elements, C = 12.01 g, H = 1.01 g, O = 16 g, and N = 14.01 g (Nubi et al., 2022).

The mass of methane (t) produced from AD is given by:

$$M_{CH_4} = \frac{16 \times A}{(M_C \times n) + (M_H \times a) + (M_O \times b) + M_N} \times 1{,}000 \quad (7)$$

$$A = 0.5n + 0.125a - 0.25b - 0.375c \quad (8)$$

The volume of methane (m^3/t), $V_{CH_4} = \frac{M_{CH_4}}{\rho_{CH_4}}$ (9)

where ρ_{CH_4} = density of methane, taken as 0.717 kg/m^3 (Ogunjuyigbe et al., 2017).

The actual volume of methane produced during the AD process is less than the theoretical volume and is expressed as 85% of the theoretical volume of methane. The actual volume of methane is taken as (Ogunjuyigbe et al., 2017):

$$V_{CH_4(Actual)} = \frac{V_{CH_4} \times 85}{100} \quad (10)$$

The electrical energy (kWh) from AD is given by:

$$E_{AD} = \frac{MSWS_{AD} \times V_{CH_4(Actual)} \times LHV_{CH_4} \times 0.85 \times \eta_{AD}}{3.6} \quad (11)$$

where $MSWS_{AD}$ is the mass of sewage sludge (in tonnes) for the AD process; LHV_{CH_4}= lower heating value of methane, 37.2 MJ/m^3 (Nubi et al., 2022); 0.85 is the capacity factor (Nubi et al., 2022); η_{AD} is the efficiency of the AD technology, 0.30 (Singh et al., 2020); 3.6 is the conversion factor from MJ to kWh.

$$MSWS_{AD} = \frac{V_{WCT} \times SWS_{CR} \times \rho_{SWS}}{1{,}000} \quad (12)$$

where SWS_{CR} = wastewater to sewage sludge conversion rate, 1% (Ijoma et al., 2022); ρ_{SWS} = density of sewage sludge (wet basis), 1 kg/l (Ozcan et al., 2015); 1,000 = conversion factor from kilogram to tonne.

The size of the generator based on the estimated electrical energy from AD is determined using:

$$P_{S(AD)} = \frac{E_{AD}}{8{,}760 \times CF}$$

where $P_{S(AD)}$ is the capacity (kW) of the plant; 8,760 is the number of hours of plant operation per annum; CF is the capacity factor, 0.85 (Ogunjuyigbe et al., 2017).

5.2.2.2 Incineration Technology for energy recovery from sewage sludge

The total energy (MJ) is calculated using equation (13):

$$TE_{INC} = LHV_{DSWS} \times MSWS_{INC} \quad (13)$$

where LHV_{DSWS} is the lower heating value of dried sewage sludge, 1,100 MJ/t (Ozcan et al., 2015).

The total mass of dried sewage sludge (in tonnes) processed for INC is calculated as:

$$MSWS_{INC} = \frac{V_{WCT} \times SWS_{CR} \times DSWS_{CR} \times \rho_{SWS}}{1{,}000} \quad (14)$$

where $DSWS_{CR}$ = dried sewage sludge conversion rate, 4.2% (Ozcan et al., 2015).

Electrical energy (kWh) from the INC technology is calculated as:

$$E_{INC} = \frac{TE_{INC} \times \eta_{INC}}{3.6} \quad (15)$$

where η_{INC} = electrical efficiency of the INC technology, taken as 20% (Nubi et al., 2022); 3.6 is the conversion factor from MJ to kWh.

The size of the INC plant based on the estimated electrical energy from INC is determined using:

$$P_{S(INC)} = \frac{E_{INC}}{8{,}760 \times CF} \tag{16}$$

where $P_{S(INC)}$ is the capacity (kW) of the INC plant; 8,760 is the number of hours of plant operation per annum; CF is the capacity factor, 0.85 (Ogunjuyigbe et al., 2017).

5.3 Economic Analysis of energy recovery technologies

Understanding the economic viability of a project is crucial to make the best investment decision in any WtE initiative. Life cycle and economic parameters were used to evaluate and compare the economic viability and sustainability of the energy recovery options. The parameters applied in this study include Life Cycle Cost (LCC), Net Present Value (NPV), Levelized Cost of Energy (LCOE), Pay Back Period (PBP), Annualised Cost of System (ACS), and Internal Rate of Return (IRR). The metrics utilised in the economic assessment of the WtE technologies are shown in Table 1.

Table 1 Indices used in the economic analysis of energy recovery technologies.

Indices	**Project lifespan (N)**	**Inflation rate (e)**	**Nominal discount rate (d_n)**	**Sale price of electricity in Nigeria (F_d)**
Value	20 years (Ogunjuyigbe et al., 2017)	21.34 % (CBN, 2022)	10 % (Ogunjuyigbe et al., 2017)	USD 0.1868/kWh (Ogunjuyigbe et al., 2017)

5.3.1 Life Cycle Cost (LCC)

The LCC (in USD) is a crucial financial life cycle metric for an investment project. It is the sum of all expenses incurred throughout the ownership and operation of a project. According to the equation below, LCC is the total investment, Operation and Maintenance (O&M) costs (Ogunjuyigbe et al., 2017).

$$LCC = C_{inv(i)} + \sum_{n=1}^{N} \frac{C_{O\&M(i)}}{(1+d_n)^n} \tag{17}$$

where $C_{inv(i)}$ is the initial cost of the investment (in USD); $C_{O\&M(i)}$ is the cost of O&M (in USD); d_n is the nominal discount rate (%); N is the project's lifespan in years.

5.3.2 Net Present Value (NPV)

The NPV (in USD) is the total present value of all the system's lifetime expenses minus the total current value of all its lifetime revenues. For economic viability, it must have a positive value. NPV is calculated as (Ogunjuyigbe et al., 2017):

$$NPV = \sum_{n=0}^{N} \frac{F_n}{(1+d_r)^n} = F_0 + \frac{F_1}{(1+d_r)^1} + \frac{F_2}{(1+d_r)^2} + \ldots\ldots\ldots + \frac{F_N}{(1+d_r)^N} \quad (18)$$

where F_n is the net cash flow rate (USD); d_r is the annual real discount rate.

The yearly net cashflow for any energy recovery system is the difference between its cash inflow and cash outflow for each year, given by equation (19):

$$F_n = R_{(i)} - C_{inv(i)} - C_{O\&M(i)} \quad (19)$$

$$R_{(i)} = E_{(i)} \times F_d \quad (20)$$

$$d_r = \left(\frac{1+d_n}{1+e}\right) - 1 \quad (21)$$

where $R_{(i)}$ is the revenue accrued from the energy recovery project (in USD); $E_{(i)}$ stands for Total Electrical Energy from each technology (kWh); F_d is the sale price of electricity in Nigeria; i is the technology of interest, i.e., INC or AD; e is the inflation rate as defined by the Central Bank of Nigeria.

5.3.2.1 Anaerobic Digestion Technology

The cost model (Hadidi and Omer, 2017) for $C_{inv(AD)}$ and $C_{O\&M(AD)}$ is presented as:

$$C_{inv(AD)} = C_{P_{(AD)}} \times P_{s_{AD}} \quad (22)$$

$$C_{O\&M(AD)} = 0.03C_{inv(AD)} + 0.005E_{AD} \quad (23)$$

where $C_{P_{(AD)}}$ is the value of the plant-specific cost for AD plants, taken as USD 4,339/kW; the O&M cost is expressed as 3% of the investment cost.

5.3.2.2 Incineration Technology

The cost model (Nubi et al., 2022) for $C_{inv(INC)}$ and $C_{O\&M(INC)}$ is given as:

$$C_{inv(INC)} = USD16{,}587 \times (P_{S(INC)})^{0.82} \quad (24)$$

$$C_{O\&M(INC)} = 0.04 \times C_{inv(INC)} \quad (25)$$

5.3.3 Levelized Cost of Energy (LCOE)

The LCOE is the lowest cost at which a system may generate electricity and break even. It can be used to benchmark the economic viability of various technologies. The lowest selling price of the produced electricity is calculated from the LCOE in USD/kWh. Equation (26) can be used to determine the LCOE for each technology (Ogunjuyigbe et al., 2017):

$$LCOE_{(i)} = \frac{LCC_{(i)}}{E_{p_{(i)}}} \times CRF_{(i)} \quad (26)$$

$$CRF = \frac{d_n(1+d_n)^N}{(1+d_n)^N-1} \quad (27)$$

where CRF is the capital recovery factor.

5.3.4 Annualised Cost of System (ACS)

The annualised cost of a project is the cost that results in the exact net present cost as the actual cash flow sequence associated with that project if it occurred evenly in every year of the project's existence. Expressed in USD/yr and calculated as (Heaps, 2022):

$$ACS = (CRF \times C_{inv}) + C_{O\&M} \quad (28)$$

5.3.5 Pay Back Period (PBP)

One of the criteria to take into account before starting a project is the PBP. It is the period (years) during which the costs of a project are recovered or when operating costs are equivalent to investment costs. It is calculated using (Nubi et al., 2022):

$$PBP_{(i)} = \frac{C_{inv(i)}(USD)}{Annual\ energy\ savings_{(i)}\ (USD/year)} \quad (29)$$

$$Annual\ energy\ savings_{(i)} = R_{(i)} - C_{O\&M_{(i)}} \quad (30)$$

5.3.6 Internal Rate of Return (IRR)

The discount rate that brings the NPV to zero is the IRR. It is approximately the maximum discount rate at which the project breaks even. The technology will be considered economically desirable only when the NPV exceeds zero and the IRR is at its highest possible level (Nubi et al., 2022).

IRR (%) = the value of d_r such that $NPV = \sum_{n=0}^{N} \frac{F_n}{(1+d_r)^n}$ (31)

5.3.7 Sensitivity Analysis

Sewage sludge generation: It is vital to analyse the effect of changes in the quantity of sludge on the economic indicators of energy recovery technologies. Therefore, the consequence of a percentage variation (±10% and ±20%) in sewage sludge processed by each technology is analysed. In essence, this analysis also indicates the effect of changes in WW generation and collection, since they are interconnected.

Nominal discount rate: Sensitivity analysis is required to determine the effect of variation in discount rates (±10% and ±20%) on cost indicators to accommodate different categories of investors.

Capital and O&M costs: This study examined the impact of a percentage shift (±10% and ±20%) in the capital and O&M costs on the overall economics of the technologies.

Electricity selling price: Therefore, an evaluation of the impact of a percentage shift (±10% and ±20%) in electricity prices on the LCC results was performed.

5.4 Results and Discussion

5.4.1 Wastewater management, sludge generation and electrical energy potential

Water access, projected wastewater generation, and collection

All the zones fall under the basic access service level based on Table 2. According to the WHO, the level of water service is grouped into no, basic, intermediate and optimal access.

Table 2. Average values of parameters used to estimate wastewater and sludge generation in the zones.

Zone	Pop.[x]	Pop.[x] growth rate (%)	Water access (l/c/d)*	WW generation (l/c/d)*	WW collection rate (%)	WW collection (l/c/d)*
NC	60,914,167	3.91	11.57	10.41	4.43	0.53
NE	45,064,191	3.22	9.67	8.70	4.90	0.41
NW	81,762,275	3.07	9.14	8.23	1.31	0.15
SE	35,611,174	2.90	9.00	8.10	9.08	0.83
SS	48,662,316	3.08	10.50	9.45	6.12	0.70
SW	65,300,488	3.20	8.00	7.20	3.53	0.23

*l/c/d - litres/capita/day; [x]Pop. - Population

The average quantity of water for the levels ranges from <5, 20, 50, to 100 l/c/d, respectively. At no access level, water for consumption is not guaranteed, and that for hygiene might be unlikely, resulting in a very high health concern. Basic access covers water for consumption, handwashing, and primary food hygiene with high health concerns. In addition to the coverage of basic access, intermediate access covers laundry and bathing with low health concerns. The optimal level meets all consumption and hygiene needs with very low health concerns (Howard and Bartram, 2003). The Federal Capital Territory (FCT) has the highest water access of 15 l/c/d, followed by Yobe, Rivers, Ogun, Kaduna, and Jigawa with 14 l/c/d. At the same time, the least was found in Ebonyi, Ekiti, Kano, and Kebbi with 5 l/c/d (FMWR et al., 2022). Generally, the NC and SW zones have the highest (11.57 l/c/d) and least (8 l/c/d) water access, respectively, across the country.

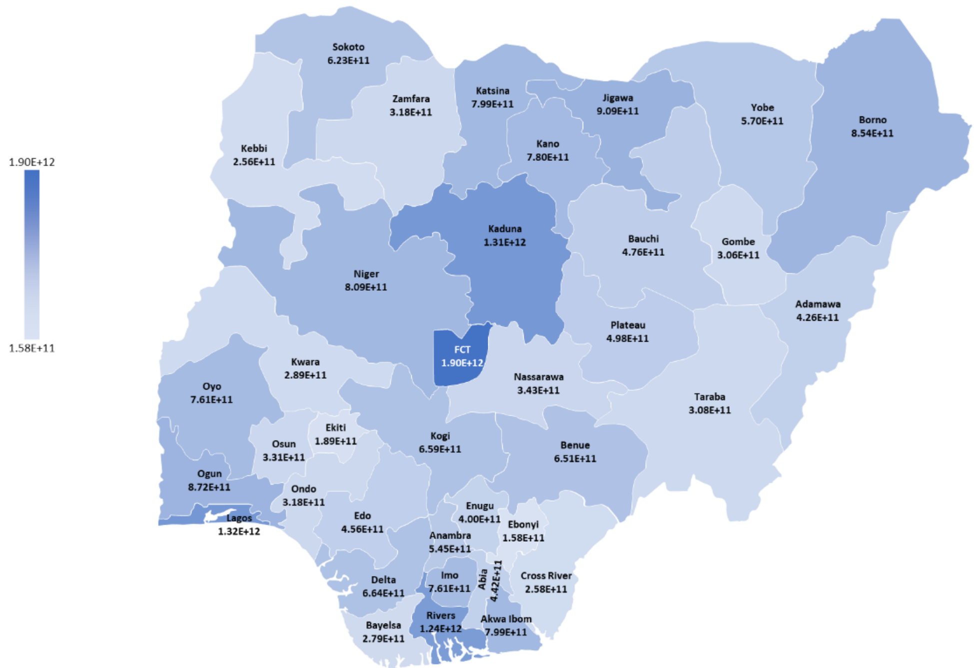

Figure 2. Estimated 20-year total wastewater generation (litres) distribution across the 36 states in Nigeria (from 2022 to 2042).

The total volume of WW generation projected for a 20-year period across Nigeria is shown in Figure 2. The results indicate that FCT has the highest WW generation, followed by Lagos and Kaduna states. This is attributed to these states being big states with high population and WW generation potential. These states have superior urbanisation and higher standards of living (Ogunjuyigbe et al., 2017). The indices signify that urban areas are critical contributors to WW generation in Nigeria. In contrast, the lowest WW generation was found in Ebonyi, Ekiti and

Cross River states, respectively. The disparity between the states with the highest and lowest WW generation potential is noteworthy. Moreover, a regional pattern indicated that Northern states such as Kaduna, Kano, and Jigawa have relatively higher WW generation potential than Southeastern states such as Abia, Enugu, and Ebonyi.

Like the scene in the states, the volume of zonal WW generation is estimated to grow with the projected population growth rate and per capita WW generation. At the zonal level (Figure 3), NC is projected to have the highest WW generation with the potential of 142.8-403.6 billion litres/yr from 2022 to 2042, followed by NW (172.4-317.1 billion litres/yr).

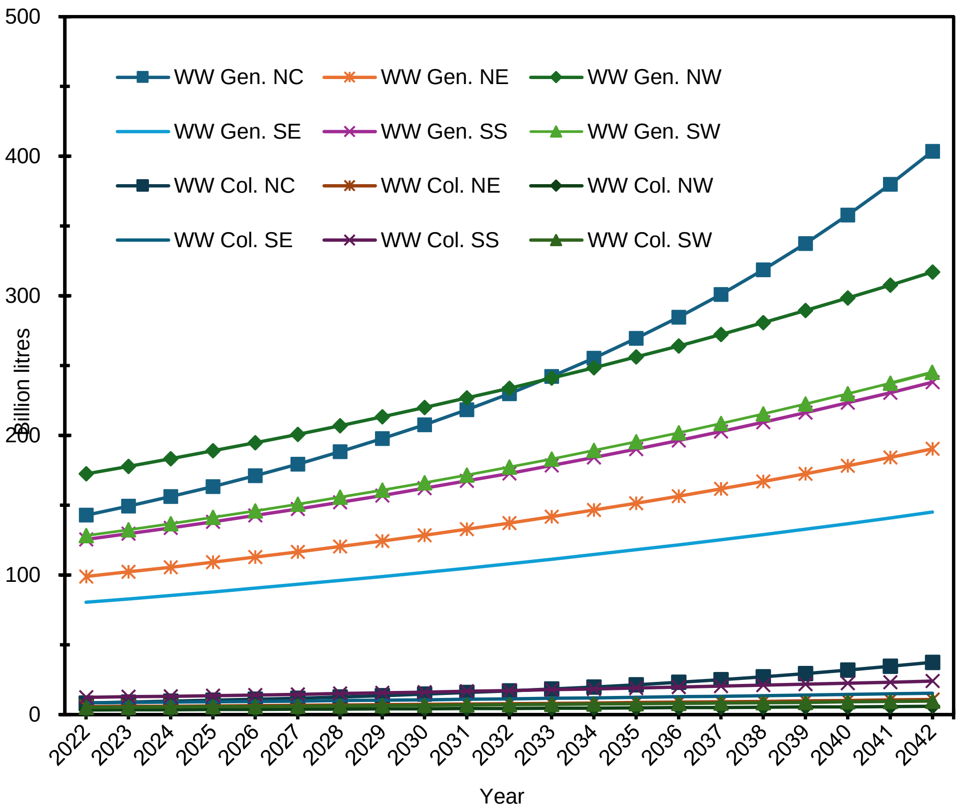

Figure 3. Comparison of projected wastewater generation and collection across the different zones in Nigeria from 2022 to 2042. (WW Gen. - wastewater generation; WW Col.- wastewater collection).

The SE and NE zones have the least potential for WW generation, with 80.5-145.1 and 98.9-190.4 billion litres/yr, respectively. In contrast, NW has the least WW collection potential ranging from 3.3 to 5.9 billion litres/yr from 2022 to 2042. Like the WW generation, NC has the highest WW collection potential with 8.3-37.5 billion litres/yr.

Although NW has higher WW generation, its WW collection is the least due to the poor coverage of the sewer network in the zone, which translates to a WW collection rate of 1.31%, which implies approximately 0.15 l/c/d, as shown in Table 2 (FMWR et al., 2022). In fact, the states with the least collection of 0% were Akwa-Ibom, Delta, Gombe, Kebbi, Ogun, and Zamfara. The maximum was 26.7% in Rivers and 15.6% each in FCT Abuja, Enugu and Imo (FMWR et al., 2022). On the other hand, the WW collection rate is highest in SE, then SS. Also, while WW generation potential peaks in the North and drops southward, WW collection climaxes down South compared to the Northern zones. Lastly, as with MSW, the projected WW generation is predicted to increase across zones due to economic and demographic growth (Nubi et al., 2022; Ogunjuyigbe et al., 2017). The estimations are based on the expectations that WW generation in NC, NE, NW, SE, SS, and SW will rise by 77.8, 47.5, 45.1, 45.4, 48.7, and 47.2%, respectively, from 2022-2042.

Sludge generation and electrical energy potential

The quantity of sludge processed for energy generation for each technology is presented in Figure 4. The potential energy generated from each technology is also shown in the different zones. Figure 4 shows that NC and SS have a higher potential for electricity while NW has the least potential. This is also directly proportional to the quantity of sludge processed at these zones. Therefore, NC and SS have the most sludge processed for energy generation, while NW has the least. The AD is the most technically feasible alternative across zones for electricity generation and is highest in NC, SS, and SE, with a potential of 6.8, 6.3, and 4.1 GWh/yr, respectively. The zones in the South demonstrated more electricity potential for AD technology compared to the northern part. Similarly, NC, SS, and SE showed higher potential for the INC scenario, while the lowest is observed in NW. The INC technology presents the lowest potential for energy generation in all zones in Nigeria. Ultimately, the electricity potential in the Southern region generally outweighs that from the Northern part for both AD and INC.

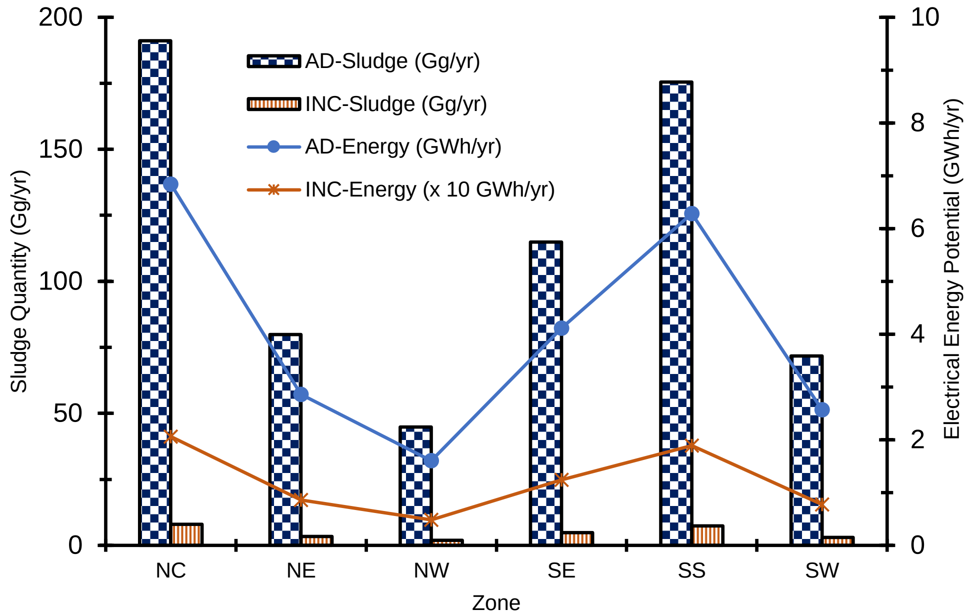

Figure 4. Projected 20-year average of sludge generation and electrical energy generation for AD and INC technology across various zones in Nigeria.

At the country level in the present study, the 20-year average WW generation is about 1,047,970,749.67 m^3/year, while 55,130,851.19 m^3/year is collected, resulting in a sludge generation of approximately 677,808.52 tonnes/year wet basis. The resulting average electrical energy potential is 24.26 and 0.73 GWh/year for AD and INC technologies, respectively. However, the county-level estimates from Jones et al. (2021) showed WW generation (industrial and domestic) of 2,289 million m^3/year, collection of 242.63 million m^3/year, and treatment of 77.71 million m^3/year. Similarly, the UN report (UN-Habitat and WHO, 2021) estimated about 2,962.368 million m^3 as the total household WW generated in 2020. Approximately 648.76 million m^3 (21.9%) of the total generation was attributed to the sewers, and 324.38 million m^3 (50%) of this volume was treated safely. In comparison, Ijoma et al. (2022) estimated that the 2017 domestic WW generation was 79.72 billion m^3, with a sludge generation of 7.97 x 10^{11} litres and an electricity potential of 46,503 GWh. The estimates of the present study were lower than those of the other studies for WW generation and collection. At the same time, the UN estimates for WW generation and collection were higher; also, the sludge generation and electricity potential were higher in Ijoma et al. (2022) than in the current study. However, the present study focused only on sewer collection, which had a maximum of approximately 27% in Rivers state (FMWR et al., 2022) and 9.08% (see Table 2) in the SE zone. Therefore, the estimations in this study may even be higher than those of other studies (Ijoma et al., 2022; Jones et al., 2021), if all collection types were considered.

The discrepancies can be attributed to differences in data sources, spatial scales, and methodologies. Jones et al. (2021) centred on aggregating country-level data from electronic databases, while Ijoma et al. (2022) used country-level domestic freshwater withdrawal data from the World Bank repository. The present study, on the other hand, utilised state-level data from FMWR et al. (2022). Furthermore, the studies might differ in the period covered, with Jones et al. (2021) providing projections based on 2015 data, Ijoma et al. (2022) focusing on 2017, and the present study spanning 2022-2042. On the one hand, the current research seems to have a more thorough and robust approach than the other two studies. It considered state-specific data, including the peculiarities and variations in different states, such as type of sanitation, accessibility to water per capita, and population. This degree of granularity in data can provide more accurate and localised estimates as the unique characteristics of different cities within the country are accounted for. Furthermore, the 20-year period in the current study may capture seasonal, annual, and cyclic variations, delivering a more reliable estimate of overall trends. On the other hand, the previous studies used data that may not capture the spatial irregularity and heterogeneity within different states. Country-level data can provide a broader viewpoint but may not account for the variations in states, which can impact the precision of the estimations. Similarly, the UN estimates were two times more than those of the present study. These estimates were based on population, water supply, water consumption, and the water consumption to WW ratio. These factors were similar to those considered in this study. However, the numerical magnitude ascribed to these factors could not be determined. Like other studies, these estimates were also unavailable at sub-national (geo-political zones, states, etc.) levels. However, estimates from these studies (Ijoma et al., 2022; Jones et al., 2021), the UN (UN-Habitat and WHO, 2021), and the present study contribute valuable information on WW generation, collection, treatment, and sludge generation in Nigeria. The variation in findings and approaches emphasises the need for further research and standardisation of data collection and reporting methods in Nigeria.

As demonstrated in the present study, the higher potential for AD energy generation is consistent with the findings of Ogunjuyigbe et al. (2017) to the extent that AD is the superior technology in Southern Nigeria, attributed to a higher fraction of the putrefiable waste stream. While in the present study, it can be attributed to a higher sewer collection rate. On the contrary, INC showed more energy potential in certain Nigerian cities for MSW (Ogunjuyigbe et al., 2017) and in India (Singh et al., 2020), Colombia (Alzate-Arias et al., 2018), and Turkey (Ozcan et al., 2015) for SWS.

5.4.2 Economic feasibility of energy recovery technologies

The economic feasibility of the WtE technologies in the various zones was evaluated based on six indicators (NPV, LCC, LCOE, IRR, PBP, and ACS) shown in Table 3.

Table 3. Economic feasibility of AD and INC technology for electricity production from the various zones in Nigeria projected over a 20-year period (2022-2042).

Zone	Tech.*	NPV (USD)	LCC (USD)	LCOE (USD/kWh)	IRR (%)	PBP (yr)	ACS (USD/yr)
NC	AD	69,580,016.62	5,296,180.99	0.280	9.09	3.55	622,087.43
	INC	1,605,093.58	338,429.90	0.094	19.30	8.89	39,751.85
NE	AD	29,056,566.15	2,211,681.47	0.280	9.09	3.55	259,783.28
	INC	605,369.87	165,383.33	0.064	22.58	11.08	19,425.86
NW	AD	16,300,713.22	1,240,751.75	0.280	9.09	3.55	145,738.24
	INC	312,157.60	102,953.43	0.046	25.06	12.92	12,092.87
SE	AD	41,838,027.26	3,184,560.38	0.280	9.09	3.55	374,057.27
	INC	912,477.40	223,007.67	0.076	21.15	10.09	26,194.40
SS	AD	63,876,518.26	4,862,051.17	0.280	9.09	3.55	571,094.71
	INC	1,460,516.29	315,508.62	0.091	19.59	9.08	37,059.52
SW	AD	26,128,934.03	1,988,840.62	0.280	9.09	3.55	233,608.47
	INC	536,629.15	151,590.23	0.061	23.02	11.39	17,805.73
		Lowest					Highest

*Tech. - Technology

The shading in the cells demonstrates how the rows compare per indicator. The light and dark shades indicated the lowest and highest values, respectively, as shown at the base of the table. The capital cost, O&M cost, and revenue aspects are also presented in Figure 5. At a glance, INC showed better outcomes in four of the six economic indicators in Table 3. The INC has higher IRR and lower LCC, LCOE, and ACS. While AD is associated with higher values of NPV and lower PBP.

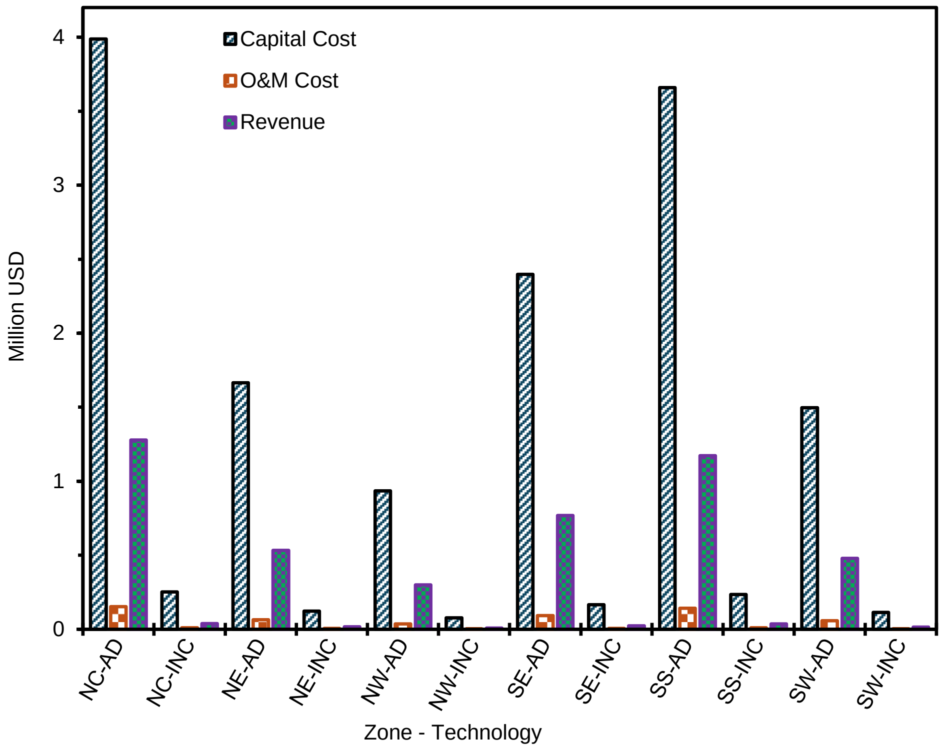

Figure 5. Capital cost, O&M cost, and revenue of AD and INC technology for electricity production from the various zones in Nigeria projected over a 20-year period between 2022-2042.

The AD technology presents the highest NPV ranging from 16.3 million USD in NW to 69.58 million USD in NC. It also has the shortest PBP of about four years across all zones. On the one hand, this makes AD financially attractive. On the other hand, AD has the highest values of LCC, ranging from 1.24 million USD in NW to 5.3 million USD in NC, the highest LCOE of USD 0.28/kWh across all zones, and the highest ACS ranging from USD 145,738.24/yr in NW to USD 622,087.43/yr in NC with lowest values of IRR of 9.09% across all zones. Hence, higher costs and lower returns reduce AD's attractiveness and make it less competitive.

Whereas for INC technology, it shows the lowest NPV from 0.31 to 1.61 million USD from NW to NC and the longest PBP, 8.89-12.92 years from NC to NW. This indicates reduced profitability and extended time to recoup investments. However, this is curtailed by the associated lower costs, as shown in Figure 5. The INC has the lowest values of LCC, ranging from 0.1 million USD in NW to 0.34 million USD in NC, lowest LCOE of USD 0.046-0.094 /kWh from NW to NC, and lowest ACS ranging from USD 12,092.87 /yr in NW to USD 39,751.85 /yr in NC.

Zone-wise Analysis

In the North, the economic analysis showed that in the NC zone, AD technology has a higher NPV of 69.58 compared to INC technology, with an NPV of 1.61 million USD. The AD also has a higher LCC of 5.3 million USD compared to 0.34 million USD for INC. The LCOE for AD is USD 0.280 /kWh, while for INC, it is USD 0.094 /kWh. The IRR for AD is 9.09% compared to 19.30% for INC. The PBP for AD is around 4 years, and 9 years for INC. The ACS for AD is 0.62 million USD/yr, while for INC, it is 0.04 million USD/yr. Similarly, in the NE zone, AD has a higher NPV of 29.06 million USD, compared to 0.61 million USD for INC. The LCOE for AD is USD 0.280 /kWh, while that of INC is USD 0.064 /kWh. AD has a higher LCC of 2.21 million USD than INC, with an LCC of 0.17 million USD. The IRR for AD is 9.09%, while that of INC is 22.58%. The PBP for AD is 3.55 years, compared to 11.08 years for INC. The ACS for AD is 0.26 million USD/yr, while that of INC is 0.02 million USD/yr. Similarly, for the NW zone, AD has an NPV of 16.3 million USD, while INC has an NPV of 0.31 million USD. AD has a higher LCC of 1.24 million USD than INC, with an LCC of 0.1 million USD. The LCOE for AD is USD 0.28 /kWh, compared to USD 0.046 /kWh for INC. The IRR for AD is 9.09%, while that of INC is 25.06%. The PBP for AD is 3.55 years, while that of INC is 12.92 years. The ACS for AD is USD 145,738.24/yr, while that of INC is USD 12,092.87/yr. Therefore, INC technology demonstrates more economic practicality in the North than AD technology. AD has a higher NPV and a shorter PBP than INC, indicating higher profitability and faster cost recovery. However, the LCC, LCOE, and ACS for AD are also higher than INC, meaning a higher startup capital and cost of electricity generation. Likewise, IRR for AD is lower than INC, thus diminishing the economic feasibility of AD against INC.

In the South, the economic analysis shows that in the SE zone, AD technology has a higher NPV of 41.84 compared to INC technology, with an NPV of 0.91 million USD. AD also has a higher LCC of 3.18 million USD compared to 0.22 million USD for INC. The LCOE for AD is USD 0.28/kWh, while for INC, it is USD 0.076/kWh. The IRR for AD is 9.09% compared to 21.15% for INC. The PBP for AD is around 4 years, and just over 10 years for INC. The ACS for AD is 0.37 million USD/yr, while for INC, it is 0.03 million USD/yr. Similarly, in the SS zone, AD has a higher NPV of 63.88 million USD, compared to 1.46 million USD for INC. AD also has a higher LCC of 4.86 million USD than INC, with an LCC of 0.32 million USD. The LCOE for AD is USD 0.28/kWh, while that of INC is USD 0.091/kWh. The IRR for AD is 9.09%, while that of INC is 19.59%. The PBP for AD is 3.55 years, compared to 9.08 years for INC. The ACS for AD is 0.57 million USD/yr, while that of INC is 0.04 million USD/yr. Likewise, AD has an NPV of 26.13 million USD for the SW zone, while INC has an NPV of 0.54 million USD. AD also has a higher LCC of 2 million USD than INC, with an LCC of 0.15 million USD. The LCOE for AD is USD 0.28/kWh, compared to USD 0.078/kWh for INC. The IRR for AD is 9.09%, while that of INC is 20.43%. The PBP for AD is 3.55 years, while that of INC is 8.45 years. The ACS for AD is USD 308,833.18, while for INC, it is USD 23,573.87. Consequently, INC technology demonstrates more economic viability in the South than AD technology. AD has a higher NPV, and a shorter PBP than INC, indicating higher profitability and faster cost recovery. However, the LCC, LCOE, and ACS for AD are also higher than INC, meaning a more increased initial investment and higher cost of electricity generation. Similarly, the IRR for AD is lower than that of INC, implying a lower return on investment.

Economic Inferences

The NPV is an indicator of the profitability of investment with time. Analysis in the present study showed that the NPV of AD technology is higher than that of INC technology for all zones in Nigeria. This implies that AD technology can be more economically viable and profitable long-term than INC technology. The total cost of the AD project, including capital costs, O&M costs, over its entire life cycle is higher than that of INC technology for all zones. This suggests that AD technology requires more initial investment than INC technology, which may be attributed to its more complex and sophisticated system design for the AD of waste. However, it is essential to note that AD technology generates higher revenue (see Figure 5) from electricity sales, compensating for its higher LCC. This is reflected in its higher NPV, indicating that AD technology can yield higher financial returns despite its higher LCC.

The cost of producing a unit kWh of electricity is more expensive for AD and cheaper for INC technology for all zones. However, both technologies have similar electricity production costs. This observation suggests that the electricity production cost is an unlikely decisive factor in the choice between AD and INC technologies in Nigeria. The rate of recouping the investment in INC technology is higher than that of AD technology for all zones in Nigeria. Investors seeking high financial returns may be more swayed by the INC technology. The superior IRR of INC technology aligns with its lower initial investment and O&M costs than AD technology, reflecting its lower LCC and ACS. Furthermore, less than 10% IRR indicates financial infeasibility (Abdallah et al., 2018). Thus, AD technology across all zones fell below 10%, while the values for INC exceeded this benchmark. Therefore, investors seeking higher returns in the short term may be interested. The INC project may take longer than AD technology to pay for itself. In addition, it falls short of the seven-year PBP threshold for an economically feasible WtE project (Mabalane et al., 2021; Nubi et al., 2022). Although AD technology has a higher initial investment, it generates more revenue from electricity sales coupled with a shorter PBP. Nevertheless, the decision power of PBP is limited, as it fails to consider the time value of money, thus a less comprehensive measure of profitability or attractiveness. As mentioned above, the INC technology in the present study rates better than AD in four (LCC, LCOE, IRR, and ACS) out of six economic indicators. However, the two indicators (NPV, PBP) where AD rates better than INC are arguably important. Similarly, in a study in Colombia, although AD had a more expensive LCOE, it was the preferred option due to the higher IRR. AD was also preferred for the WtE system using MSW based on better NPV, LCOE, and PBP (Ogunjuyigbe et al., 2017). On the contrary, INC was more economically feasible for the generation of energy from MSW in Nigeria (Nubi et al., 2022) with lower LCC, LCOE, and higher IRR. However, AD had higher NPV and shorter PBP. A feasibility study in the United Arab Emirates (UAE) determined that INC is more financially feasible than AD as INC had a better IRR, a lower Profitability Index (PI) , and a lower LCOE (Abdallah et al., 2018). Similarly, INC was chosen over AD in Oman based on higher NPV and lower LCOE. However, AD had favourable PI, PBP, and IRR (Abushammala and Qazi, 2021).

Therefore, the selection between AD and INC technologies should reflect the fiscal goal and priorities of the project. Suppose that the focus is on shorter PBP and faster recovery of the initial investment. In that case, AD technology may be preferred due to its relatively shorter PBP compared to INC technology. However, INC technology may be more viable if the project has a longer-term perspective emphasising lower initial capital costs.

5.4.3 Sensitivity Analysis

The outcomes of the sensitivity analyses are presented in Figure S1 – S10 (in the supplementary information) of appendix B.

The NPV, LCC, and ACS show direct proportionality to SWS production changes for the AD technology, as illustrated in Figure S1. A 20% decrease in SWS production resulted in a 20% decrease in NPV, while a 20% increase in SWS production led to a 20% increase in the three parameters. In all zones, a change in SWS production resulted in a change of equal magnitude in NPV, LCC, and ACS. Thus, NPV, LCC, and ACS show a moderate sensitivity to changes in SWS production. Figure S1 also depicts the insensitivity of IRR, LCOE, and PBP to changes in SWS production in all zones. NPV, LCC, IRR, and ACS show a directly proportional relationship to changes in SWS production for INC technology. A 20% decrease in SWS production led to a 21.87-22.9% decrease in NPV, while a 20% increase in SWS production led to a 22.2-23.45% increase in NPV, as presented in Figure S2. For IRR, it was 8.21-15.34% and 6.83-12.65%. The resulting changes in ACS are relatively constant (e.g., 16.72 for a 20% decrease in SWS production). It is also fairly constant (e.g., 4.1 and 5.6%, respectively, for a 20% decrease in SWS production) but inversely proportional for LCOE and PBP. In all zones, a change in SWS production resulted in a slightly higher magnitude in NPV and less in LCOE, PBP, IRR, LCC, and ACS, respectively. Thus, NPV, LCC, and ACS show a moderate sensitivity to changes in SWS production and low sensitivity for IRR, PBP, and LCOE. Therefore, NPV, LCC, and ACS are sensitive, while IRR, LCOE, and PBP are insensitive to changes in SWS production for AD technology. On the contrary, NPV is more susceptible to changes in SWS production for INC technology than LCC, ACS, and IRR, respectively, while LCOE and PBP are marginally insensitive.

The impact of changes in the nominal discount rate on the economic feasibility of AD and INC technologies are shown in Figure S3 and Figure S4, respectively. For both AD and INC technologies, the resultant changes in NPV and LCC are inversely proportional to changes in the nominal discount rate. However, the magnitudes are high and low for NPV and LCC, respectively. Whereas LCOE shows a directly proportional relationship, the resulting magnitude is two times less than the causal. On the other hand, IRR, PBP, and ACS remained unchanged despite changes in nominal discount. Therefore, NPV is more sensitive to changes in nominal discount than LCC and LCOE. While IRR, PBP, and ACS are unaffected for both technologies. But INC showed more sensitivity compared to AD technology.

The effect of fluctuations in capital cost on the economic feasibility of AD and INC technologies are shown in Figure S5 and Figure S6, respectively. For AD technology, IRR, LCOE, and PBP remained unaffected regardless of variations in capital cost. However, NPV, LCC, and ACS show a positive linear relationship in magnitude and direction to the changes in capital cost. All six parameters were affected by changes in capital cost for INC technology, as represented in Figure S6. However, the average magnitude was highest for NPV, similar for LCC and ACS compared to PBP and LCOE. Additionally, regardless of the direction of change in capital cost, NPV, LCC, IRR, and ACS decreased while LCOE and PBP increased. Therefore, NPV, LCC, and ACS are sensitive to changes in capital cost, while IRR, LCOE, and PBP are unchanged for AD. In comparison, NPV was very sensitive to changes in capital cost for INC, followed by LCC, ACS, IRR, and LCOE, while PBP was the least.

The effect of variations in O&M cost on the economic feasibility of AD and INC technologies are illustrated in Figure S7 and Figure S8, respectively. For AD technology in Figure S7, the resulting changes in IRR, LCOE, and PBP are negligible. However, NPV, LCC, and ACS showed a positive linear relationship in magnitude and direction to the changes in capital cost. Like the case of capital cost, all six parameters were altered by changes in O&M cost for INC technology, as represented in Figure S8. However, the resultant changes were directly proportional for NPV, LCC, IRR, and ACS but inversely proportional for LCOE and PBP. In addition, the average magnitude was highest for NPV, similar for LCC and ACS compared to PBP and LCOE. Altogether, NPV, LCC, and ACS are sensitive to changes in O&M cost, while IRR, LCOE, and PBP are unchanged for AD technology. Moreover, NPV was very sensitive to changes in O&M cost for INC, followed by LCC, ACS, IRR, and LCOE, while PBP was the least. All parameters were generally affected more by changes in the capital than O&M cost.

The influence of variations in the selling price of electricity on the economic feasibility of AD and INC technologies are displayed in Figure S9 and Figure S10, respectively. The LCC, LCOE, and ACS are unaffected by changes in electricity selling prices for both technologies. For AD technology, NPV and IRR show a positive linear relationship in magnitude and direction to the changes in electricity tariff. But PBP shows a negative linear relationship. Also, the average magnitude was highest for PBP and similar for NPV and IRR, respectively. However, NPV and IRR show a positive linear relationship in magnitude and direction for INC technology, as represented in Figure S10. But PBP shows a negative linear relationship. Also, the average magnitude was highest for IRR than PBP and NPV, respectively. Overall, PBP, NPV, and IRR are sensitive in that order to changes in electricity selling price for AD. The order for INC is IRR, PBP, and NPV. However, both technologies do not influence LCC, LCOE, and ACS.

Ultimately, among the economic viability indicators, NPV demonstrated the most sensitivity to changes in SWS production, nominal discount, costs, and electricity selling price. Similarly, INC proved to be more sensitive among the two technologies. The NPV, LCC, and ACS are sensitive to changes in SWS production, while LCOE and PBP are relatively insensitive for both technologies. Changes in the nominal discount rate significantly impact NPV for both technologies, with INC technology being more sensitive. Capital costs have a notable influence on the indicators compared to O&M costs, with NPV being particularly sensitive to changes in capital costs for INC technology.

Regarding electricity selling prices for both technologies, PBP, NPV, and IRR are sensitive, while LCC, LCOE, and ACS are generally unaffected. The outcome of the sensitivity analysis is consistent with the study in the UAE, where the capital, O&M cost, and the electricity tariff had a low impact on the NPV of AD but a high impact on INC (Abdallah et al., 2018). A study in South Africa concluded that discount rate, capital cost, and energy price have a high effect on the NPV of AD (Mabalane et al., 2021). The sensitivity analysis implies that WtE systems will be more economical if more SWS is generated and measures are put in place to limit the costs as much as possible. At the same time, the electricity tariff does not drop below the current price.

5.4.4 General Implications and Limitations

There may be uncertainties or limitations in the analysis presented in the context of the study or discussion. Certain assumptions were made during the investigation, which could be scrutinised. These assumptions may affect the accuracy, reliability, or generalizability of the findings or conclusions drawn from this study.

Firstly, it is assumed that the households sampled in the base data (FMWR et al., 2022) represent Nigeria's total population. Wastewater generation is taken as 90% of water use, but other studies were established at 80-90% (Ijoma et al., 2022; Ozcan et al., 2015). Water accessibility, collection rate, population growth rate, capital cost, and O&M cost remained constant over the 20-year period. Additionally, variabilities in investment cost and O&M cost can impact the general economics of WtE technologies. Other expenses such as labour, taxes, and transportation were assumed equal in both scenarios and, therefore, ignored.

In addition, the sludge used in AD is not dewatered, while the sludge used in INC is dewatered and dried. However, the energy used in the dewatering and drying was not considered in the study: which would impact the net energy production. The average values for the LHV of sludge and methane were adopted from sources in the literature. At the same time, a more robust study will involve a proximate and ultimate analysis of the sludge samples from the locations.

Furthermore, the technologies were compared in a mutually exclusive scenario. The comparison assumed that only one technology at a time was used without considering the possibility of using both technologies simultaneously. Therefore, future studies can explore any potential synergy between both and other WtE systems, as well as the co-processing of SWS with MSW. The co-digestion and co-firing of SWS with MSW or agricultural waste materials can enhance the overall organic content thus improving biogas production and combustion in AD and INC, respectively. Other aspects that can be explored in future to tackle the challenges of low heating value and high moisture content of SWS include optimised dewatering using centrifugation, belt press or thermal drying. These processes enhance the organic content of SWS and decrease the moisture content. Process optimization of the AD and INC technologies should also be considered.

Moreover, value recovery from co-products of WtE systems can be an essential aspect of the overall economic feasibility and sustainability of such systems. For instance, recyclable materials recovered from waste streams can be sold or reused, generating additional revenue or reducing waste disposal costs. Digestates from AD can be used as fertilisers in agriculture, potentially providing a valuable source of nutrients for crop growth. Disregarding the possible value recovery opportunities in the economic analysis of WtE systems may result in an incomplete assessment of their overall economic viability and sustainability. Therefore, including a comprehensive analysis of value recovery from co-products in the future could offer a more holistic evaluation of the economic feasibility of WtE systems. Additionally, this analysis focused solely on economic and technical considerations without considering the potential environmental impacts, social implications, or sustainability aspects of the WtE technologies. Environmental pollution, resource depletion, social equity, community impacts, and other social and environmental factors can be contemplated in future studies.

Finally, government support and policy implementation influence the successful performance of WtE projects. Clear legislation and policy enforcement strategies are needed to create an environment that encourages local and foreign investors to participate in AD and INC projects. Financial institutions should be strengthened, and adequate incentives such as subsidies and carbon credits should be provided to attract private sector investments. Integrating WtE systems into existing policies, such as the REMP and the National Environmental Sanitation Policy (NESP), can further support their implementation while increasing energy access. For example, these WtE technologies can contribute to the achievement of SDGs such as clean energy, economic growth, responsible consumption and production, and sustainable cities and communities. But it should be acknowledged that the implementation of WtE policies in Nigeria is still developing and encounters poor implementation challenges. However, informed decision-making through economic analysis and the integration of appropriate sustainable WtE technologies, as part of an integrated MSW management strategy, can support the achievement of the environmental, social, and economic goals outlined in various SDGs.

5.5 Conclusion

Estimated potential generation of wastewater and sewage sludge was carried out in various zones of Nigeria. The electrical energy potential and economic viability of WtE technologies (AD and INC) were examined. It was revealed in the study that the zones in the North had the highest potential for WW generation, but the southern parts were superior in terms of sewer collection rate. Consequently, the North Central zone is predicted to have the highest wastewater generation and collection potential of 142.8-403.6 and 8.3-37.5 billion litres/yr from 2022 to 2042. The zones with the least wastewater generation and collection potential were South East (80.5-145.1 billion litres/yr) and North West (3.3-5.9 billion litres/yr), respectively. However, the estimates obtained at the national level were less than the UN estimates.

Furthermore, there was a positive linear relationship between sludge generation and electricity potential; AD presented the best technological option, while the North Central zone had the highest generation potential of 6.8 GWh/yr. Finally, in terms of economic feasibility, INC technology showed more feasibility than AD. INC had lower LCC, LCOE, and ACS values and a higher IRR. Still, AD had a competitively higher NPV and shorter PBP. Based on the sensitivity analysis results, the NPV is very sensitive to changes in cost, discount rate, and electricity tariff, especially for INC technology.

CRediT authorship contribution statement

Charles Amarachi Ogbu: Conceptualisation, Methodology, Writing original draft, Writing - review & editing, Data curation, Statistical analysis. **Tatiana Alexiou Ivanova**: Conceptualisation, Methodology, Resources, Supervision, Funding acquisition, Writing - review & editing. **Temitayo Abayomi Ewemoje**: Methodology, Supervision, Writing -review & editing. **Chinedu Osita Okolie**: Statistical analysis, Writing –review & editing. **Hynek Roubík**: Conceptualisation, Methodology, Resources, Supervision, Funding acquisition, Writing - review & editing.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data
Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2023.166554. See Appendix B

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6. Evaluation of Treatment Efficiency, Effluent Quality Indices, and Greenhouse Gas Emissions of a Wastewater Treatment Plant in Abuja, Nigeria

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Abstract

Monitoring wastewater treatment plants (WWTPs) is of crucial public health and environmental concern, as captured in Sustainable Development Goal 6. This study evaluated the performance of a WWTP using the pollutant removal efficiency, wastewater quality index (WWQI) and effluent quality index (EQI). Temporal and seasonal variations in effluent quality were examined using analysis of variance and principal component analysis. The onsite and offsite greenhouse gas (GHG) emissions were also quantified using emission factors. Removal efficiency was higher in the dry season for pH, SO_4, and COD, while the rainy season favoured DO, NH_4-N, and PO_4 removal. Sustainable measures must be implemented to achieve increased and steady removal of NO_3-N, FCC, and BOD, as their effluent concentrations were inconsistent in meeting statutory limits. The WWQI showed better WWTP performance during the rainy season, while EQI indicated the dry season. The mean values of EQI and WWQI were 343,058.59 kg/month and 39.08, respectively. Mean value of GHG emissions was 7,270.75 t CO_2-eq./year, with onsite treatment contributing 82.3%. Electricity consumption was the primary source of offsite emissions. The WWTP had an intensity of 1.05 kg CO_2-eq./m^3 influent and 1.98 kg CO_2-eq./kg PU removed, with an electricity use of 10,192.15 kWh/d. This study offers stakeholders and policymakers a snapshot of GHG emissions from the Nigerian water sector.

Keywords: Carbon Footprint; Water Quality; Water Pollution; Electricity Use; Global Warming Potential; Sewage Treatment.

6.1 Introduction

The Sustainable Development Goals of the United Nations aim to ensure access to water and sanitation for all by 2030 (UN, 2022). The treatment of wastewater is crucial to the achievement of Sustainable Development Goal 6. Unfortunately, more than 80% of wastewater is discharged into the environment without adequate treatment (UN Water, 2022). In large cities of low and middle-income countries, insufficient safe drinking water and sanitation pose significant public health challenges (FMWR et al., 2022; Ogbu et al., 2023a). Inadequate sewage treatment is one of the main contributors to water pollution in Nigeria, with approximately 46% of the population and 17% of household members having access to basic sanitation services (FMWR et al., 2022; Ogbu et al., 2023a). Additionally, 11% of households reported recent diarrhoea cases (FMWR et al., 2022). Basic water, sanitation, and hygiene services were accessible to only 10% of the population, while 23% practised open defecation (FMWR et al., 2022). Consequently, inadequate sewage treatment is one of the main contributors to water pollution in developing countries.

Water and sanitation services, vital for society, industry, and the environment, are highly regulated. Non-compliance with discharge regulations can lead to legal actions, fines, and economic burdens due to remediation efforts and healthcare costs. In many developing countries, discharge regulations are rarely met, and achieving compliance involves economic and environmental consequences (UNEP 2016; WWAP 2017). The operations of wastewater treatment plants (WWTP) have environmental impacts, notably the emission of greenhouse gases (GHG), which contributes to global warming (Corominas et al., 2013). Effluent volatilisation can lead to air pollution, particularly with volatile organic compounds and certain gases. Poor river water quality, linked to health hazards such as high sodium and salinity, poses risks to communities. The effluent pollutants harm the quality of the water and aquatic life in rivers and lakes, leading to eutrophication, algae blooms, habitat degradation, loss of biodiversity and ecosystem imbalances. Hence, uncontrolled WWTP activities pose significant hazardous impacts on humans and the environment.

The performance of WWTP is influenced by population characteristics, living conditions, economic advancement (Li et al., 2021), ambient temperature, discharge standards, electricity tariffs, and geo-morphological attributes (e.g., elevation, altitude). Other factors include the industrial outlook (Cardoso et al., 2021), electricity mix (Wang et al., 2016), technology, scale, policy, and governance issues (Longo et al., 2016). The WWTPs, classified as high energy consumers (UNEP, 2016; WWAP, 2017), contribute to environmental pollution through the consumption of fossil fuel energy (Li et al., 2021). The performance of WWTPs in urban African cities has been extensively studied to ensure compliance with standards (Makuwa et al., 2022; Ibangha et al., 2024), understand public health risks, and compare different systems (Ogwueleka and Samson, 2020). The motivation was to forecast WWTP efficiency (Balogun and Ogwueleka, 2023) and elucidate the overall impact on environmental sustainability (Balogun and Ogwueleka, 2021). The efficiency of various systems in removing organic matter, solids, coliforms, heavy metals, and nutrients was investigated (Balogun and Ogwueleka, 2023, 2021; Okafor and Olawale, 2020). The variation in the efficiency of these WWTPs has been statistically examined using correlation, t-test, and analysis of variance (ANOVA) (Ibangha et al., 2024; Iheukwumere et al., 2021). However, multivariate analyses, notably principal component analysis (PCA) (Giordani, 2018), offer a powerful tool to explore complex datasets. However, multivariate analyses, notably Principal Component Analysis (PCA) (Giordani, 2018), offer a powerful tool for exploring complex WWTP datasets, especially high-dimensional, multivariate data. The PCA complements traditional statistical methods, providing a holistic view of data patterns and relationships. It has been applied to monitor temporal trends in effluent characteristics (Ebrahimi et al., 2017; Platikanov et al., 2014) and determine the effect of wastewater parameters on CH_4 production (Enitan et al., 2018). The PCA has been extensively used to study seasonal and temporal variation (Aduojo et al., 2024; Elemile et al., 2021), distribution, occurrences, and sources of pollution and the associated risks (Anifowose et al., 2024; Ezeudu et al., 2024; Jolaosho et al., 2024), as well as predicting the performance of a potable water treatment plant (Abba et al., 2020). Despite its potential, the use of PCA in evaluating WWTP performance in low and middle-income countries, especially in African cities, is in its early stages. However, recent studies have begun to employ PCA to establish relationships between wastewater parameters and identify processes with optimum efficiency in industrial WWTPs (Nwoko et al., 2023). Therefore, integrating PCA into WWTP assessments can support data-driven decision-making, enable continuous improvement of WWTP processes, and address the unique environmental challenges in most African cities.

Furthermore, effluent quality is typically evaluated based on multiple parameters aligned with statutory discharge limits (FAO, 2003; NESREA, 2011, 2009). The water quality index (WQI) emerges as a key performance indicator, condensing diverse variables into a single unitless score, simplifying information on water quality, and facilitating comparison. The strengths and weaknesses of WQIs have been documented in the evaluation of different water sources (including WWTP effluents) in developing countries for drinking, irrigation, domestic and industrial use (Ahsan et al., 2023; Aljanabi et al., 2021; Chidiac et al., 2023; Uddin et al., 2021). The suitability of several surface water sources (Anani and Olomukoro, 2021; Iwegbue et al., 2023; Jolaosho et al., 2024; Ogundairo et al., 2024) and groundwater sources (Elemile et al., 2021; Ezechinyere and Stanislaus, 2023; Taiwo et al., 2023) as sources of drinking water in Nigeria was assessed using the weighted arithmetic water quality index (WAWQI) (Iwegbue et al., 2023; Jolaosho et al., 2024; Ogundairo et al., 2024) and the national sanitation foundation water quality index (Kalagbor et al., 2019). Another indicator is the effluent quality index (EQI), which systematically defines effluent quality (Jeppsson et al., 2007). The EQI was applied to optimise WWTPs based on layout (De Ketele et al., 2018) and altitude (Baquero-Rodríguez et al., 2022). Therefore, adopting EQI and WQI can provide easy-to-understand metrics to assess and manage WWTP effluents.

Stringent discharge limits can heighten GHG emissions, necessitating consideration of both environmental impacts and emissions in creating standards (Zhou et al., 2022). Estimation of the characteristics of GHG emissions and future mitigation potentials of WWTPs is crucial for achieving carbon neutrality (Yang et al., 2023). It may become a determining factor in selecting WWTP technology, considering stricter policies and treaties such as the Kyoto Protocol (Bani Shahabadi et al., 2010). The GHG emissions from WWTP operations have three primary sources: direct (scope 1) emissions related to biological processes in wastewater and sludge treatment, indirect (scope 2) emissions from electricity or thermal energy consumption, and indirect external (scope 3) emissions from value chain activities not directly controlled onsite (e.g., offsite sludge disposal, chemical production, and transportation) (Mannina et al., 2016a; Wu et al., 2022).

The estimation of GHG emissions from WWTPs is broadly accomplished using the modelling or the emission factor methods (Liu et al., 2024). The primary GHG emissions from WWTPs include CO_2, CH_4, and N_2O, with 100-year Global Warming Potential (GWP) of 1, 28, and 265 CO2-eq., respectively (IPCC, 2014). According to IPCC guidelines (2019), CO_2 from onsite operations is excluded due to its biogenic origin and insignificant adverse impacts. However, pollutants in wastewater may contain both fossil and biogenic carbon, emphasising the importance of estimating GHG emissions from all sources for a comprehensive understanding of carbon flows (Wang et al., 2022). The source of wastewater, geographical location, treatment scales, technologies and configuration, electricity consumption, sludge production (Lam et al., 2020; Ogbu et al., 2023b; Wu et al., 2022), seasonal changes (Masuda et al., 2015), and electricity consumption (Chen, 2019) significantly influence GHG emissions. Optimisation of WWTP capacity usage reduces energy losses and GHG emissions (Yapıcıoğlu and Demir, 2021). Layouts of WWTPs impact emissions, with potential 60-65% reductions through advancements (Tong et al., 2024). The anaerobic-anoxic-oxic and oxidation ditch processes exhibit lower direct emission intensities than biofilm and sequencing batch reactors (Zhou et al., 2022). Biogas recovery reduces emissions by up to 13.4%, lowering the adverse impacts of fossil fuels (Bani Shahabadi et al., 2010; Keller and Hartley, 2003). Biosolid management and disposal methods influence GWP values (Lam et al., 2020; Wu et al., 2022), with wastewater and sludge treatment processes contributing 23-83% to the overall carbon footprint and 1-13% to the disposal of offsite sludge (Wu et al., 2022). Sludge drying contributes 22-59% to total GHG emissions, while anaerobic digestion reduces it by about 12-38%. Landfill sludge disposal has higher GHG emissions than incineration, composting, and agricultural use (Wu et al., 2022).

Additionally, previous reviews highlighted that the GHG emission and environmental profile of water facilities are understudied in African cities (Gallego-Schmid et al., 2019; Diaz-Elsayed et al., 2020; Lam et al., 2020). It is not unconnected to awareness levels, resource constraints, and the enforcement level of policies and regulations (Karkour et al., 2021; Ogbu et al., 2023b). The synthesis of recent water and wastewater treatment-related life cycle assessment (LCA) studies in Africa highlighted GWP as the most popular impact category. It can be linked to the political and social significance of GWP in support of the international climate change mitigation agenda (Corominas et al., 2013). The GWP correlated with energy use intensity and the source of water treated. Moreover, a significant number of studies were in Northern and Southern Africa, while West African countries were underrepresented (Ogbu et al., 2023b). However, environmental assessments such as LCA are evolving in West Africa (Karkour et al., 2021; Maepa et al., 2017; Harding et al., 2021), but related information on the water sector is currently unavailable, particularly in Nigeria.

Therefore, quantifying direct and indirect GHG emissions from WWTPs in African cities is essential for understanding environmental consequences and developing mitigation strategies. Consequently, the objectives of this study are (i) to evaluate the performance of a WWTP based on the pollutant treatment efficiency (TE) and the effluent quality indices, (ii) to examine the temporal characteristics of the WWTP efficiency, and (iii) to estimate the GHG emissions from WWTP operations.

6.2. Materials and Methods

6.2.1 Study location

The Wupa WWTP is in the Idu Industrial area of Abuja, Nigeria. It lies between latitudes 70' 201" and 90' 201"N and longitudes 60' 451" and 70' 391"E close to the Wupa River (Francis and Ndububa, 2022). The WWTP is an activated sludge process type (Balogun and Ogwueleka, 2021), operates below its design capacity of 131,250 m^3/day, and is powered by diesel generators. During the study period, the average daily inflow and outflow during the dry season were 12,000 m^3/d and 10,080 m^3/d; for the rainy season, they were 24,000 m^3/d and 21,120 m^3/d, respectively. It was intended to serve a population of 700,000 and expandable to 1,000,000. It comprises the preliminary (screw pumps, screens, grit, and scum removal), secondary (aeration basins, secondary clarifiers), tertiary (UV disinfection), and sludge treatment (gravity thickener, dewatering, and drying bed). The temperature in the area ranges from 27°C to 36°C with a mean value of 29°C (Balogun and Ogwueleka, 2021). Abuja is in Nigeria's central region, with the most significant rainfall from April to October and a minimum from November to March (World Bank, 2021). Secondary data acquired from the Wupa WWTP is used in this study. The dataset comprised the mean monthly characteristics of untreated (influent) and treated (effluent) from 2014 to 2017 and 2019 to 2021. The parameters include Chemical Oxygen Demand (COD), Biochemical Oxygen Demand (BOD_5), Total Suspended Solids (TSS), Dissolved Oxygen (DO), Faecal Coliform Count (FCC), Total Coliform Count (TCC), pH, Ammonium Nitrogen (NH_4-N), Nitrate Nitrogen (NO_3-N), Nitrite Nitrogen (NO_2-N), Phosphate (PO_4), Sulphate (SO_4), Iron (Fe^{2+}), and Chloride Ion (Cl^-) content.

6.2.2 Wastewater treatment efficiency and Quality Indices

6.2.2.1 Treatment efficiency

The percentage treatment (removal) efficiency of each wastewater characteristic was calculated as:

$$TE, \% = \frac{(C_{in} - C_{out}) * 100}{C_{in}} \quad (1)$$

Where, C_{in} and C_{out} are the influent and effluent concentrations of pollutants, respectively.

6.2.2.2 Effluent water quality Indices

The EQI was used to determine the total mass of pollution unit (PU) (kg PU) in the discharged effluent. The model was adapted from Longo et al. (2016). This approach aims to measure the effluent pollution load of substances that significantly impact the health of the recipient. The EQI (kg PU/month) adopted in this study is given by:

$$EQI = \frac{1}{1{,}000\,(t_f - t_i)} * \sum_{t_f}^{t_i} [COD_{out} + BOD_{out} + TSS_{out} + NH_{4\,out} + NO_{3\,out} + NO_{2\,out} + PO_{4\,out}] * Q_{out} \quad (2)$$

Where, COD_{out}, BOD_{out}, TSS_{out}, $NH_{4\,out}$, $NO_{3\,out}$, $NO_{2\,out}$, and $PO_{4\,out}$ are the effluent concentration of COD, BOD, TSS, NH_4-N, NO_3-N, NO_2-N, and PO_4 expressed in mg/l and Q_{out} (m^3 effluent/month) is the effluent flow rate and t time. 1,000 is conversion factor from mg/l to kg/m^3.

The WAWQI was used to determine the wastewater quality index (WWQI). The WAWQI is a unit-less qualitative method that cumulatively describes an aggregated set of measured water quality parameters (Ahsan et al., 2023; Chidiac et al., 2023). The parameters considered include COD, BOD_5, TSS, DO, FCC, TCC, pH, NH_4-N, NO_3-N, NO_2-N, PO_4, SO_4, Fe^{2+}, and Cl^-. The WAWQI is given as (Ahsan et al., 2023; Chidiac et al., 2023):

$$WAWQI = \frac{\sum Q_n W_n}{\sum W_n} \quad (3)$$

$$Q_n = 100 * \frac{[V_n - V_0]}{[S_n - V_0]} \quad (4)$$

$$W_n = \frac{k}{S_n} \quad (5)$$

$$k = \frac{1}{\sum(\frac{1}{S_n})} \quad (6)$$

Where, Q_n and W_n are the quality rating and unit weight for the nth parameter, respectively. k is the constant of proportionality. V_n is the observed value of the nth parameter. V_0 is the ideal value of the nth parameter in pure water (Ideal value for pH = 7, DO =14.6 mg/l (Iwegbue et al., 2023), and zero (0) for all other parameters). S_n is the standard permissible value of the nth parameter. The allowable values used in this study were adopted from local (NESREA, 2011, 2009) and international (FAO, 2003) standards for effluent discharge to surface water bodies.

6.2.3 Statistical Analyses

Descriptive statistics were used to analyse the features associated with the EQI, WWQI, and TE. Two-way ANOVA and Tukey test were used to verify the differences in these variables over time (year) and seasons. The Pearson correlation analysis was used to analyse the relationships between variables. The

PCA was employed to capture significant patterns and variations in the TE over time and seasons. The suitability of the dataset for PCA was tested using the Bartlett sphericity test. The descriptive statistics, ANOVA, Tukey test, and Pearson correlation were conducted using Origin Software. The Bartlett sphericity test and PCA were performed using the R functions BARTLETT {EFAtools} (Steiner and Grieder, 2020) and PCA {FactoMineR} (Lê et al., 2008), respectively.

6.2.4 Estimation of GHG emissions

The GHG emissions were estimated using the emission factor methodology, mainly from the Tier 1 conditions of the IPCC (2019) guidelines. For onsite GHG emissions, the wastewater and sludge treatment line were considered. Onsite emissions from sludge treatment were considered a component of wastewater treatment and discharge (IPCC, 2019). Emissions from the transportation and disposal of sludge were not explicitly considered. The GHG emissions considered were CO_2, CH_4 and N_2O. Electricity consumption and chemical use in sludge treatment were considered for offsite emissions.

6.2.4.1 Onsite emissions from biological (wastewater and sludge) treatment line

The quantity of onsite CH_4, N_2O, and CO_2 emissions was estimated as follows:

$$CH_{4_{IPCC\_bio}} = ((BOD_{in} - S_{BOD}) * EF_{IPCC_{bio,CH4}} - R_{CH_4}) * 28$$ (IPCC, 2019) (7)

$$N_2O_{IPCC\_bio} = (TN_{in} * EF_{IPCC_{bio,N_2O}}) * 265$$ (IPCC, 2019) (8)

$$S_{BOD} = S_{mass} * K_{rem} * 1{,}000$$ (IPCC, 2019) (9)

$$CO_{2_{bio}} = EF_{bio,_{CO_2}} * COD_{removed}$$ (Wang et al., 2022) (10)

$$COD_{removed} = (COD_{in} - COD_{out}) * Q_{in}$$ (Wang et al., 2022) (11)

Where, $CH_{4_{IPCC\_bio}}$ (kg CO_2-eq./yr) and $N_2O_{IPCC\_bio}$ (kg CO_2-eq./yr), and $CO_{2_{bio}}$(kg CO_2/yr) are emission estimation for CH_4, N_2O, and CO_2 from centralised aerobic treatment plants. $EF_{IPCC_{bio,CH4}}$ (0.018 kg CH_4/kg BOD) and $EF_{IPCC_{bio,N_2O}}$ (0.016 kg N_2O/kg TN influent) (IPCC, 2019), and $EF_{bio,_{CO_2}}$(0.56 kg CO_2/kg COD removed) (Wang et al., 2022) are CH_4, N_2O, and CO_2 emission factors of centralised aerobic treatment plants. BOD_{in} (kg BOD influent/yr) is the annual mass of influent BOD. S_{BOD} (kg BOD/yr) = organic component removed from wastewater (in the form of sludge) in aerobic treatment plants. TN_{in} (kg TN effluent/yr) is the annual mass of effluent Total Nitrogen (TN). S_{mass} (tonnes/year) = amount of raw sludge removed from wastewater treatment as dry mass. S_{mass} was estimated based on TSS, according to Andreoli et al. (2007), see Supplementary Material in Appendix C (Section S3). K_{rem} (1.16 kg BOD/kg dry mass sludge) = sludge factor for aerobic WWTPs without separate primary sedimentation (IPCC, 2019). 1,000 = conversion factor for tonnes to kilograms. R_{CH_4} is the quantity of CH_4 recovered or flared equal to zero in this study. The 100-year GWP values for CO_2, CH_4, and N_2O are 1, 28, and 265, respectively (IPCC, 2014). $COD_{removed}$ (kg COD/year) is the COD removed at the WWTP. COD_{in} (kg COD influent/yr) and COD_{out} (kg COD effluent/yr) are the annual mass of influent and effluent COD, respectively. Q_{in} (m^3 influent/yr) is the annual influent flow.

6.2.4.2 Offsite emissions from discharge pathways (into rivers)

The quantity of offsite CH_4, N_2O, and CO_2 emissions was estimated as follows:

$$CH_{4_{IPCC\_eff}} = EF_{IPCC_{CH4\_eff}} * BOD_{out} * 28 \quad \text{(IPCC, 2019)} \quad (12)$$

$$N_2O_{IPCC\_eff} = EF_{IPCC_{N_2O\_eff}} * TN_{out} * 265 \quad \text{(IPCC, 2019)} \quad (13)$$

$$CO_{2_{bio\_eff}} = EF_{bio,_{CO_2\_eff}} * COD_{out} \quad \text{(Wang et al., 2022)} \quad (14)$$

Where, $CH_{4_{IPCC\_eff}}$ (kg CO_2-eq./yr), $N_2O_{IPCC\_eff}$ (kg CO_2-eq./yr), and $CO_{2_{bio\_eff}}$ (kg CO_2/yr) are emission of CH_4 and N_2O, and CO_2 from discharge to aquatic environments. $EF_{IPCC_{CH4\_eff}}$ (0.068 kg CH_4/kg BOD effluent), $EF_{IPCC_{N_2O\_eff}}$ (0.005 kg N_2O/kg TN effluent), (IPCC, 2019) and $EF_{bio,_{CO_2\_eff}}$ (0.5709 kg CO_2/kg COD effluent) (Wang et al., 2022) are emission factors for CH_4, N_2O, and CO_2 of discharge to aquatic environments. BOD_{out} (kg BOD effluent/yr) and TN_{out} (kg TN effluent/yr) are the annual mass of effluent BOD and TN.

6.2.4.3 Offsite emissions from electricity consumption

The quantity of offsite CH_4, N_2O, and CO_2 emissions from electricity consumption was estimated as follows (Chen, 2019; Mannina et al., 2016b):

$$CH_{4_{ec}} = EF_{IPCC,_{CH_4\_diesel}} * E_D \quad (15)$$

$$N_2O_{ec} = EF_{IPCC,_{N_2O\_diesel}} * E_D \quad (16)$$

$$CO_{2_{ec}} = EF_{IPCC,_{CO_2\_diesel}} * E_D \quad (17)$$

Where, $CH_{4_{ec}}$ (kg CO_2-eq./yr), N_2O_{ec} (kg CO_2-eq./yr), and $CO_{2_{ec}}$ (kg CO_2/yr) are CH_4, N_2O, and CO_2 emissions from electricity consumption. $EF_{IPCC,\, CH_{4\_diesel}}$ (10 kg CH_4/TJ of diesel), $EF_{IPCC, N_2O_{\_diesel}}$ (0.6 kg N_2O/ TJ of diesel), and $EF_{IPCC,\, CO_{2\_diesel}}$ (74,100 kg CO_2/TJ of diesel) are IPCC (2006) emission factors for CH_4, N_2O, and CO_2 for electricity generation from diesel. E_D (TJ/yr) is the total electricity demand, assumed constant during the study period, and estimated as the product of the electricity consumption rate and the annual influent flow (m^3/yr). The WWTP electricity consumption rate (kWh/m^3) was adapted from Longo et al. (2016), see Supplementary Material in Appendix C (Section S2).

6.2.4.4 Offsite emissions from chemical consumption.

The offsite emission from chemical usage was estimated using Chen (2019):

$$GHG_{chemical} = \sum(EF_i * m_i) \tag{18}$$

Where, $GHG_{chemical}$ (kg CO_2-eq./yr) is the GHG emission linked to chemical usage, m_i is the dosage of chemical used in kg/yr, and EF_i is the emission factor of chemical i. The EF_i value of polymer was 1.5 kg CO_2-eq./kg (Liang et al., 2021).

6.3. Results and Discussion

6.3.1 Wastewater treatment efficiency

The dataset was examined for Seasonal patterns: dry (November to March) and rainy (April to October) between 2014-2017 and 2019-2021. Tables 1 and 2 show the descriptive statistics of the TE and effluent concentration of pollutants. Significant values were taken at $p<=0.1$. Results are presented in reduced form; the supplementary material in Appendix C contains expanded results in Tables S1 to S10 and FigureS1.

Organic matter and solids

The WWTP achieved high TE of 87.8±10.2%, 91.1±7%, and 91.6±3.5% for COD, BOD, and TSS, respectively, as shown in Table 1. Discharge values of 28.3±17.2, 10.4±8.4, and 14.4±5.0 mg/l, respectively, were within acceptable ranges. Compliance with standards (FAO, 2003; NESREA, 2011, 2009) was mainly observed, except for maximum BOD values. The COD removal was significantly ($p< 0.01$) higher during the dry seasons, with the highest in 2016 and lowest in 2021 ($p<0.0001$), with significant ($p<0.01$) interactions between season and year. The BOD removal peaked in 2017 and plunged in 2015 ($p<0.0001$), with significant ($p<0.05$) interactions between season and year. The TSS removal was highest in 2017 ($p<0.005$) and lowest in 2021.

Table 1. Summary statistics of the treatment efficiency of pollutants.

	Overall				Year							Season	
Parameters	n	Mean	Min.	Max.	2014	2015	2016	2017	2019	2020	2021	Dry	Rainy
pH	84	2.49	-4.29	9.46	3.74	0.74	4.11	1.61	2.82	-0.06	4.45	3.28	1.92
DO	84	-139.44	-677.78	0	-104.29	-145.47	-66.85	-157.85	-187.04	-210.6	-103.94	-181	-109.75
NO_3-N	84	-267.09	-1820	33.33	-344.52	-326.09	-396.21	-139.8	-324.7	-123.6	-214.69	-202.11	-313.51
NO_2-N	48	-85.2	-2959.82	94.51	10.7	23.17	-7.36	-367.29	-	-	-	2.45	-147.8
NH_4-N	84	-32.28	-655.56	98.86	-163.19	-73.86	58.23	-17.71	-12.13	-67.74	50.4	-111.38	24.21
PO_4	84	18.49	-358.97	81.11	22.49	-19.5	50.97	-4.86	19.79	18.91	41.64	8.87	25.36
Cl^-	48	13.71	-29.63	42.86	15.3	8.34	13.09	18.09	-	-	-	15.39	12.5
SO_4	48	12.9	-29.63	45.46	22.11	13.68	10.77	5.06	-	-	-	15.91	10.76
Fe^{2+}	48	47.29	-138.94	91.91	46.8	58.66	57.05	26.66	-	-	-	47.3	47.29
BOD	84	91.05	69.25	99.34	92.31	84.13	91.8	96.93	92.32	89.49	90.38	90.61	91.37
TSS	84	91.63	76.15	98.42	92.87	89.66	90.55	94.21	92.88	91.74	89.47	91.56	91.68
COD	84	87.81	49.95	98.77	92.33	81.27	84.2	95.75	92.33	87.94	80.85	90.61	85.81
TCC	48	97.41	75	100	97.92	97.08	98.24	96.4	-	-	-	97.41	97.41
FCC	84	96.26	82.5	100	97.83	97.3	99.09	99.31	94.72	93.6	91.98	95.39	96.89

Table 2. Summary statistics of the effluent concentration of pollutants.

		Overall				Year							Season		Standard	
Parameters	Units	n	Mean	Min.	Max.	2014	2015	2016	2017	2019	2020	2021	Dry	Rainy	Limits	Source
pH	unitless	84	7.10	6.50	7.50	7.08	7.295	7.08	7.00	7.08	7.17	6.99	7.08	7.12	5.5-9	(NESREA, 2009)
DO.	mg/l	84	6.79	4.40	7.60	6.57	6.8	6.94	6.64	6.80	6.83	6.95	6.72	6.84	min. 4	(FAO, 2003)
NO_3-N	mg/l	84	6.34	0.70	*15.00	5.45	5.71	7.48	6.03	6.08	4.98	8.67	6.10	6.52	10	(FAO, 2003)
NO_2-N	mg/l	48	0.39	0.02	5.20	0.18	0.22	0.38	0.79	-	-	-	0.32	0.44	10	(NESREA, 2011)
NH_4-N	mg/l	84	2.45	0.10	9.00	3.08	3.19	1.42	1.44	2.30	3.10	2.62	3.32	1.83	50	(NESREA, 2009)
PO_4	mg/l	84	1.80	0.17	4.00	1.64	1.91	2.07	1.52	1.77	1.53	2.18	1.95	1.70	5	(NESREA, 2011)
Cl^-	mg/l	48	32.59	20.00	55.00	32.75	35.04	32.23	30.33	-	-	-	30.92	33.79	600	(NESREA, 2011)
FCC	MPN/100 ml	84	56.48	0.00	*280.00	33.5	43.17	14.55	9.25	69.42	97.25	128.25	70.65	46.36	200	(FAO, 2003)
TCC	CFU/100 ml	48	67.44	0.00	390.00	71.17	98.17	52.5	47.92	-	-	-	88.1	52.68	400	(FAO, 2003)
COD	mg/l	84	28.31	7.00	75.00	18.58	46.43	30.29	17.00	18.58	32.48	34.78	27.01	29.23	250	(NESREA, 2009)
TSS	mg/l	84	14.36	3.60	41.50	14.26	18.28	11.76	11.75	14.25	16.30	13.89	15.04	13.87	100	(NESREA, 2009)
BOD	mg/l	84	10.37	2.00	*42.00	8.15	21.13	7.68	4.66	8.14	13.05	9.80	12.68	8.72	30	(NESREA, 2009)
Fe^{2+}	mg/l	48	0.61	0.04	2.70	0.54	0.58	0.55	0.77	-	-	-	0.54	0.67	20	(NESREA, 2011)
SO_4	mg/l	48	33.90	21.00	50.00	32.08	33.5	35.09	34.92	-	-	-	32.45	34.93	500	(NESREA, 2011)

* - exceeds limits

There was no significant difference across seasons, but the TE was higher during the rainy seasons. The TE showed no significant seasonal difference but was higher during rainy seasons. The high TE of organic pollutants and solids aligns with previous studies (Balogun and Ogwueleka, 2021; Iheukwumere et al., 2021; Makuwa et al., 2022; Ogwueleka and Samson, 2020). Diverse temporal and seasonal impacts on TE were evident. Higher COD removal during the rainy season was attributed to higher dilution by precipitation (Makuwa et al., 2022). The removal of BOD and COD was better in the rainy season, while TSS removal was better in the dry season. Unlike TSS, the removal of BOD and COD varied substantially across seasons (Iheukwumere et al., 2021).

Microbial load

Microbial load TE was 97.4±3.8% and 96.3±3.9%, with mean discharge values of 67.4±70.1 CFU/100 ml and 56.5±61.4 MPN/100 ml for TCC and FCC, respectively. Table 2 shows that the mean discharge values were within limits. However, the maximum FCC concentration exceeded the limits. There was no significant difference across seasons and years, but TCC removal was higher during the rainy seasons. It was highest in 2016 and lowest in 2017. The FCC removal was significantly ($p<0.05$) higher during the rainy seasons. The FCC removal was highest in 2017 and lowest in 2021 ($p<0.0001$). Coliform removal was also very high in previous studies (Balogun and Ogwueleka, 2021; Ibangha et al., 2024; Iheukwumere et al., 2021; Makuwa et al., 2022). However, like in the present study, effluent concentration exceeded the limits in earlier reports (Ibangha et al., 2024; Makuwa et al., 2022). Temporal and seasonal influence on coliform removal were also recorded (Iheukwumere et al., 2021; Makuwa et al., 2022). Makuwa et al. (2022) attributed high effluent concentrations of E. coli to temperature and flow rate changes despite 99% removal in the wet season.

Nutrients

Nutrient removal varied with NO_3-N, NO_2-N, NH_4-N, and PO_4^{3-} showing efficiency of -267.1±365.1%, -85.2±463.7%, -32.3±168.9%, and 18.5±54%, respectively (see Table 1). Mean discharge values of 6.3±2.9, 0.4±0.81, 2.5±2.1, and 1.8±0.61 mg/l, respectively, were within limits. However, the maximum NO_3-N concentration exceeded these limits, as shown in Table 2. Previous studies emphasised the need for enhanced nutrient removal techniques at this WWTP, especially for nitrate (Balogun and Ogwueleka, 2021). Although no significant seasonal or yearly differences were observed, the removal of NO_3-N and NO_2-N was higher during the rainy season, peaking in 2020 and 2015 and lowest in 2016 and 2017. Significant differences were observed in NH_4-N ($p<0.0005$) and PO_4^{3-}

($p<0.01$) removal over the years. In 2016, the removal of NH_4-N and PO_4^{3-} was the highest, while the lowest values were in 2014 and 2015, respectively.

The removal of NH_4-N was significantly ($p<0.0001$) higher during the rainy season, while PO_4^{3-} removal was higher but not significantly different during the rainy season. The increase in nitrate concentration is consistent with prior findings (Platikanov et al., 2014), while others reported higher nutrient removal, particularly for NH_4-N and phosphate (Iheukwumere et al., 2021; Makuwa et al., 2022). Makuwa et al. (2022) recorded higher removal for both in the rainy season, while Iheukwumere et al. (2021) reported higher phosphate removal in the rainy season and nitrate and NH_4-N in the dry season.

Other water quality indicators

The TE of 2.5±3.0%, -139.4±118.4%, 13.7±14.0%, 12.9±14.3%, and 47.3±49.2% (see Table 1) with mean discharge values of 7.1±0.2, 6.8±0.4 mg/l, 32.6±7.6 mg/l, 33.9±8.8 mg/l, and 0.61±0.5 mg/l were obtained for pH, DO, Cl^-, SO_4, and Fe^{2+}, respectively. All mean values were within limits, as shown in Table 2. The negative value of DO removal is desirable as it implies increased oxygenation leading to pathogen elimination due to the activities of Aerobacter (Balogun and Ogwueleka, 2021). Oxygenation was significantly ($p<0.005$) higher during the rainy seasons, peaked in 2020 and dipped in 2016 ($p<0.05$). It likely favoured the removal of organic pollutants and microbial load as previously obtained (Balogun and Ogwueleka, 2021; Iheukwumere et al., 2021). Iheukwumere et al. (2021) noted a superior pH and DO treatment in the rainy season. Ibangha et al. (2024) ascribed DO variations to salinity, air pressure, and water temperature. The control of pH was notably higher during the dry season, peaking in 2021 and lowest in 2020 ($p<0.0005$). Similarly, SO_4 removal was significantly higher during dry seasons, with peak in 2014 and lowest in 2017 ($p<0.05$). The TE of pH was significantly ($p<0.05$) higher during the dry season. It was highest in 2021 and lowest in 2020 ($p<0.0005$). The removal of SO_4 was significantly ($p<0.05$) higher during the dry seasons. It was highest in 2014 and lowest in 2017 ($p<0.05$). There was no significant seasonal or yearly difference in the removal of Cl^- and Fe^{2+}, with higher values during the dry season.

6.3.2 Effluent Quality Indices

The average WWQI values of influent and effluent are shown in Table 3. The overall average WWQI of 39.08 demonstrates an effluent of good quality. The effluent parameters were mostly within the statutory requirements. In 2020 and 2014, the effluent WWQI was significantly ($p<0.05$) the best, while it was the poorest in 2021 and 2015. There were no significant differences between seasons, but the effluent quality was better during the rainy season. Generally, the effluent is categorised as good. However, more treatment is needed before final discharge into rivers and surface waters, especially concerning parameters that fail to meet the limits. The effluent of this study is unsuitable for domestic use and may pose health risks to the public. Perhaps a better index can be obtained if the effluent concentration of pollutants is consistently maintained below the permissible limits.

Table 3. Average WWQI characteristics of influent (inf.) and effluent (eff.)

		Inf. WWQI	Eff. WWQI	Eff. Remark
	Overall	70.87	39.08	Good
Year	2014	67.83	37.41	Good
	2015	70.61	41.21	Good
	2016	75.42	40.94	Good
	2017	74.08	37.68	Good
	2019	66.69	37.69	Good
	2020	68.12	36.41	Good
	2021	73.35	42.19	Good
Season	Dry	76	39.9	Good
	Rainy	67.2	38.49	Good

The average EQI characteristics within the period under study are shown in Table 4. The average EQI was 31,744.98 kg PU/month. The dry seasons had a significantly ($p<0.0001$) better effluent quality. The effect of seasonal changes on WWTP performance is evident.

Table 4. Average EQI characteristics of influent and effluent.

Period	Inf. EQI (kg PU/month)	Eff. EQI (kg PU/month)	PU removed (kg/month)	% removal
2014	328,309.90	24,345.74	303,964.15	92.24
2015	340,854.95	45,763.70	295,091.25	85.50
2016	289,547.20	33,083.73	256,463.47	88.19
2017	468,664.87	22,025.57	446,639.29	95.01
2019	328,803.56	24,464.49	304,339.07	92.27
2020	362,310.86	35,337.74	326,973.12	89.94
2021	282,918.80	37,193.90	245,724.90	86.12
Dry Season	249,971.50	20,321.19	229,650.32	91.08
Rainy Season	409,549.37	39,904.84	369,644.53	89.05
Overall	343,058.59	31,744.98	311,313.61	89.90

Similarly, the best effluent quality was observed in 2017 (22,025.57 kg PU/month) and 2014 (24,345.74 kg PU/month), while the worst was in 2015 (45,763.70 kg PU/month) and 2021 (37,193.90 kg PU/month), at $p<0.0001$. The EQI reflects the high TE of organic pollutants, although the TE of nutrients was very low. Consequently, most plants performed optimally during spring compared to summer and worse in winter. This was attributed to changes in environment and temperature, especially in biological treatment plants where variations were acceptable (Arabzadeh et al., 2023).

6.3.3 Correlation Analysis

The Pearson product-moment correlation was applied to each pair of TE and water indices to identify possible associations presented in Table 5. For comparison, the correlation was also performed for a scenario when the missing observation values were filled with the average of the parameters; the result is presented in Table S1. However, only Table 5 is commented on. Lower values of EQI and WWQI indicate better effluent quality. The EQI negatively correlated with BOD, TSS, and COD removal, indicating the influence of organic matter and solids on effluent quality. Comparably, WWQI showed a negative correlation with NO_3-N and a positive with pH and EQI. However, the ideal value for DO and pH is not zero, as is the case for other parameters. Hence, pH correction positively correlates with PO_4, BOD, TSS, and COD removal, indicating pH adjustment enhances their removal and contributes to overall effluent quality.

The efficiency of oxygenation (treatment of DO) positively correlates with PO_4, TCC, and FCC removal. It implies that sufficient dissolved oxygen is crucial for the biological processes responsible for phosphorus removal by activated sludge. Similarly, adequate oxygen is essential for maintaining aerobic conditions that support microbial activities for the biodegradation of organic matter and coliforms. Additionally, the efficient removal of pathogens is related to increased Aerobacter activity due to higher DO levels (Balogun and Ogwueleka, 2021), indicating better effluent quality. The removal of BOD positively correlates with the removal of TSS and COD, while COD removal positively correlates with TSS removal. The interconnection between BOD, COD, and TSS suggests that improvements in organic matter removal coincide with enhanced removal of solid particles. Biological treatment methods, such as activated sludge or biological filters, play a pivotal role in achieving these positive correlations by simultaneously targeting multiple pollutants. The removal of Fe^{2+} negatively correlates with SO_4 and positively with the removal of NH_4-N, TCC, and FCC. Meanwhile, FCC removal positively correlates with TCC removal.

Table 5. #Pearson correlation coefficients of TEs and indices.

	pH	DO	NO_3-N	NO_2-N	NH_4-N	PO_4	Cl^-	SO_4	Fe^{2+}	BOD	TSS	COD	TCC	FCC	WWQI	EQI
pH	1.0															
DO	0.0	1.0														
NO_3-N	-0.1	-0.2	1.0													
NO_2-N	0.1	0.0	0.1	1.0												
NH_4-N	0.0	0.0	0.0	-0.1	1.0											
PO_4	0.2**	0.2*	0.0	0.0	0.2**	1.0										
Cl^-	0.1	-0.1	0.1	-0.1	-0.2	0.0	1.0									
SO_4	0.0	0.2	0.0	0.2	-0.3**	0.1	-0.2	1.0								
Fe^{2+}	0.0	0.2	-0.2	0.0	0.2	-0.1	0.0	0.0	1.0							
BOD	0.3***	0.0	-0.1	-0.2	0.1	0.0	0.1	-0.3**	-0.1	1.0						
TSS	0.2*	0.0	-0.2**	0.0	-0.1	-0.1	0.2	-0.1	-0.1	0.5***	1.0					
COD	0.2*	-0.2*	0.0	-0.1	-0.1	-0.2	0.1	-0.1	-0.1	0.5***	0.6	1.0				
TCC	0.0	0.4***	-0.1	0.0	0.0	0.1	0.0	0.0	0.4***	0.1	0.1	0.0	1.0			
FCC	0.1	0.3**	-0.1	0.0	-0.1	-0.1	0.0	-0.2	0.0	0.3**	0.3***	0.2	0.4***	1.0		
WWQI	0.3**	0.0	-0.4***	-0.2	0.0	0.0	0.0	0.1	0.2	-0.2	-0.1	-0.2	0.1	-0.1	1.0	
EQI	-0.2**	0.2*	-0.1	-0.1	0.2**	0.1	-0.2	0.1	0.1	-0.5***	-0.3***	-0.6***	-0.1	-0.1	0.3***	1.0

*** Correlation is significant at 0.01 level; **Correlation is significant at 0.05 level; * Correlation is significant at 0.10 level.

#Correlation matrix was computed based on the number of pairs with non-missing data (pairwise deletion of missing data).

This inverse relationship suggests that the mechanisms involved in removing Fe^{2+} may be ineffective in concurrently removing SO_4, indicated by the TE of 45% and 14.7% for Fe^{2+} and SO_4, respectively. However, the positive correlation suggests an increase in Fe^{2+} removal is associated with higher removal of NH_4-N and coliforms.

6.3.4 Principal Component Analysis

The PCA was performed for the fourteen variables corresponding to the TE of water quality parameters. The variables were normalised to a mean of zero (0) and unit variance. Seven PCs were extracted with cumulative variance explained >70%. Extraction is recommended at eigenvalues >1 (Ebrahimi et al., 2017; Nwoko et al., 2023) or cumulative variance >70% (Giordani, 2018).

Table 6 shows that the PCs explained 73.43% of the variability in the dataset. The parameters with loading >0.4 in magnitude on any PC denote high correlation (Ebrahimi et al., 2017).

Table 6. ₹Extracted principal components (PC) and their loadings.

	Principal Components						
Parameters	PC1	PC2	PC3	PC4	PC5	PC6	PC7
pH	0.38			0.60*			
DO		0.66*				-0.41*	
NO_3-N		-0.39			0.43*		0.60*
NO_2-N			0.40*				0.56*
NH_4-N			-0.78*				
PO_4				0.75*			
CL-					0.75*		
SO_4			0.64*				
Fe^{2+}		0.59*		-0.38		0.51*	
BOD	0.78*						
TSS	0.82*						
COD	0.75*						
TCC		0.68*					
FCC	0.49*					-0.46*	
Eigenvalue	2.51	1.74	1.46	1.39	1.16	1.06	0.97
Initial Variance (%)	17.95	12.44	10.42	9.89	8.25	7.58	6.90
Cumulative Variance (%)	17.95	30.39	40.81	50.70	58.96	66.53	73.43

[*] - high correlation; [₹] missing values are imputed as the mean of the variable.

The dimensions were reduced from 14 variables to 7 components with a nominal 26.57% loss of information. A similar model with six PCs was attributed to independence between variables (Platikanov et al., 2014). The correlation matrix of the PC scores illustrated in Table S2 showed off-diagonal elements near zero, indicating the relative independence of PCs. The PC1, accounting for 17.95% of the variance in the dataset, represented organic pollutants and microbial activity likelihood. The PC2 explained 12.44% of the variance and correlated strongly with oxygen levels, iron concentration, and bacterial contamination. The PC3 explained 10.42% of the total variance associated with nutrient removal, particularly NO_2-N, NH_4-N, and SO_4. The PC4 mainly correlated with phosphate and pH, while PC5 connected to NO_3-N and Cl^-. The PC2 and PC6 incorporated oxygenation performance and the removal of pathogens and iron.

The scores for the extracted PCs were analysed for the study period to understand the wastewater characteristics. The temporal variation of the PC scores is illustrated in Figure S1 in the supplementary material in Appendix C. The PC1, PC3, and PC4 show higher amplitudes and larger fluctuations than others. They exhibit relatively larger positive and negative values. However, PC2, PC5, PC6, and PC7 have smaller amplitudes and fluctuate less. The PC1, PC2, and PC5 have more positive scores in rainy seasons and more negative scores during dry seasons. Consequently, parameters showing positive loading on these components have higher TE during the rainy season than in the dry season. Therefore, the removal of COD, BOD, TSS, FCC, DO, Fe, TCC, nitrate, and Chlorine was higher during the rainy season. The PC3, PC4, and PC6 have more positive scores in dry seasons and more negative scores during rainy seasons. Therefore, during the dry season, the removal of NO_2-N, sulphate, pH, phosphate, and Fe was higher, while that of NH_4-N, DO, and FCC was higher during the rainy season. The PC1 scores were consistently positive in 2017, reflecting the highest TE for organic and microbial loading. Similarly, PC2 showed elevated oxygenation and removal of iron and coliforms in 2016. On the contrary, PC3 indicated the lowest nutrient and sulphate removal rates in 2021. Generally, there were more positive scores in the rainy season and in 2016 and 2014, indicating better WWTP performance. These trends suggest a higher WWTP activity in rainy seasons, possibly due to increased municipal activity and influent flow (Platikanov et al., 2014).

6.3.5 Total GHG emissions

The onsite GHG emissions generated by the wastewater treatment line and the offsite GHG emissions by electricity consumption, effluent discharge, and chemical consumption were estimated as CO_2 equivalent in this study. The total GHG emissions released by the WWTP were compared with findings from earlier related studies. The total GHG emissions from all sources were disaggregated except for chemical usage.

6.3.5.1 Onsite GHG emissions

The total and average GHG emissions from onsite and offsite sources over the 7-year period were 50,895.1 t CO_2-eq. and 7,270.8 t CO_2-eq./yr, respectively, as shown in Figure 1.

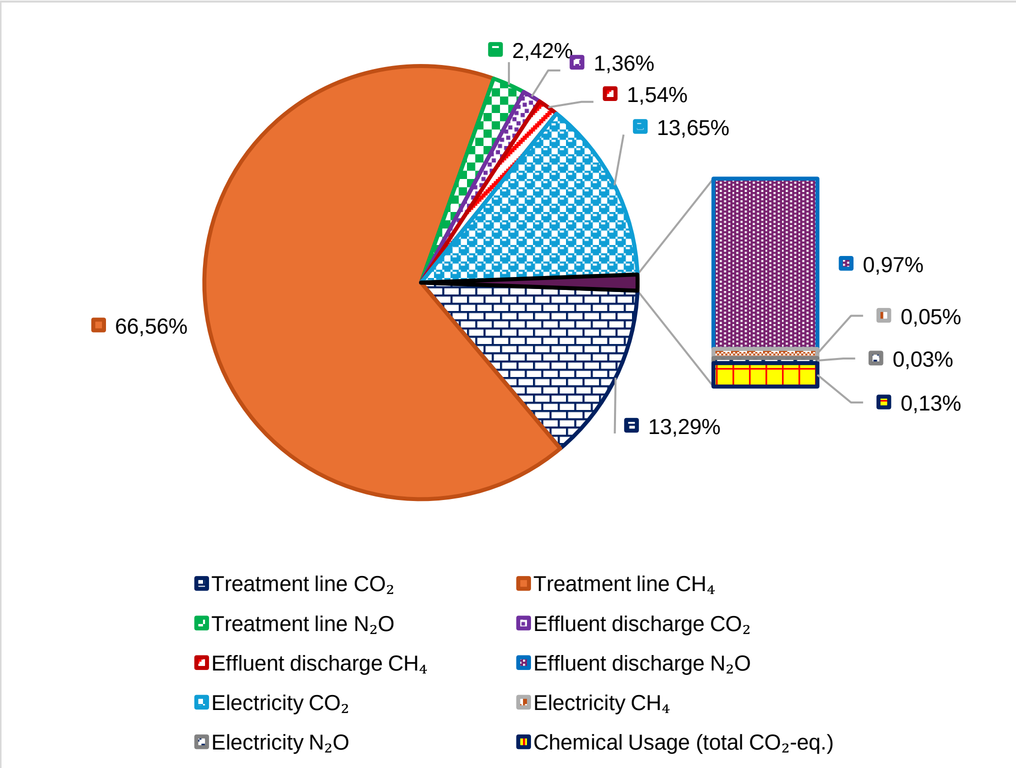

Figure 1. GHG emission generations from different onsite and offsite sources in the wastewater treatment process.

The treatment line is the major source of GHG production, constituting 82.3% of total emissions. Methane makes up 68.15% of total emissions. It is primarily attributed to GHGs released during aeration (Kyung et al., 2015) and partly to the absence of a primary clarifier (Kyung et al., 2020). The removal of carbonaceous materials and nutrients in the aeration basins releases GHG emissions (Kyung et al., 2015). Additionally, limited oxygen in anoxic zones fosters denitrifying bacteria, leading to N_2O production and emission during aerobic processes (IPCC, 2019). Moreover, methane can be directly emitted due to its insolubility (Kyung et al., 2015). Direct GHG emissions are temperature dependent (Yapıcıoğlu and Demir, 2021), influenced by solid retention times (SRT) (Campos et al., 2016), influent characteristics, and DO (Ogbu et al., 2023b). Higher temperatures increase CH_4 emissions (Yapıcıoğlu and Demir, 2021), specifically in aeration

(Masuda et al., 2015) and coagulation–flocculation tanks (Yapıcıoğlu and Demir, 2021). Anaerobic conditions in treatment stages, such as sewage conveyance, increase CH_4 and CO_2 generation in aerobic systems (IPCC, 2019). They are released during aeration (Daelman et al., 2012). These potentially low emissions can be significant for large-scale sewers (Willis, 2017).

6.3.5.2 Offsite GHG emissions

In this study, the percentage composition of CO_2, CH_4, and N_2O in the total GHG emissions were 28.3%, 68.15%, and 3.42%, respectively, while polymers used in sludge dewatering contributed 0.13%. Electricity use was the principal (48.53%) source of CO_2 emissions, while most CH_4 (97.67%) and N_2O (70.72%) emissions stem from the treatment line. Electricity consumption and effluent discharge contributed the most to offsite GHG emissions. The estimated average energy consumption of the WWTP was 0.54 kWh/m^3, equivalent to 10,192.15 kWh/d. Electricity consumption covered 77.44% of total offsite GHG emissions, an average of 998,262.54 kg CO_2-eq./yr. The emission of CO_2 constitutes most (up to 99.41%) of these emissions. The greatest electricity consumption (details in Tables S6 and S7) was ascribed to anoxic mixers (35.42%), oxidation blowers (29.83%), and UV lamps (20.51%). It amounts to 3,610, 3,040, and 2,090 kWh/d of electricity consumption, corresponding to 968.71, 815.76, and 560.83 kg CO_2-eq./d of GHG emissions, respectively. The effluent discharge into adjacent rivers accounted for 21.81% of total offsite GHG emissions, reaching an average of 281,089.29 kg CO_2-eq./yr. Methane emissions constitute most (up to 39.73%) of these emissions. Introducing treated effluent into rivers and streams contains residual organic matter as reflected in the BOD, COD, and TSS. According to Short et al. (2017, 2014), there is a potential for releasing dissolved CH_4 and N_2O in effluent discharges in rivers. Moreover, their production strongly correlates with the condition of the aquatic environment (Smith et al., 2017).

The contributions of CO_2, CH_4, and N_2O to overall GHG emissions over multiple years are shown in Figure 2. Temporal GHG emission trends reveal fluctuations, with peaks in 2017 and 2020 and declines in 2014 and 2019. Methane dominates with over two-thirds of annual emissions, suggesting its importance in mitigating total emissions. Temporal variability indicates that factors like technology changes and operational practices influence emissions, linked to TE that are affected by electricity consumption and chemical use. Efficiency indicators related to electricity usage and PU removed show high TE in 2017, resulting in increased total GHG emissions, as shown in Figure 3.

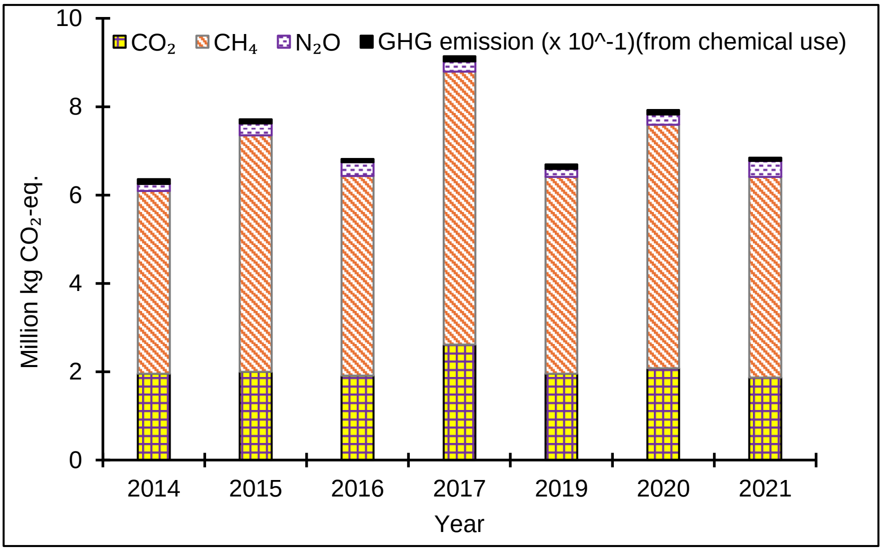

Figure 2. GHG emission generations over a 7-year period at the wastewater treatment process.

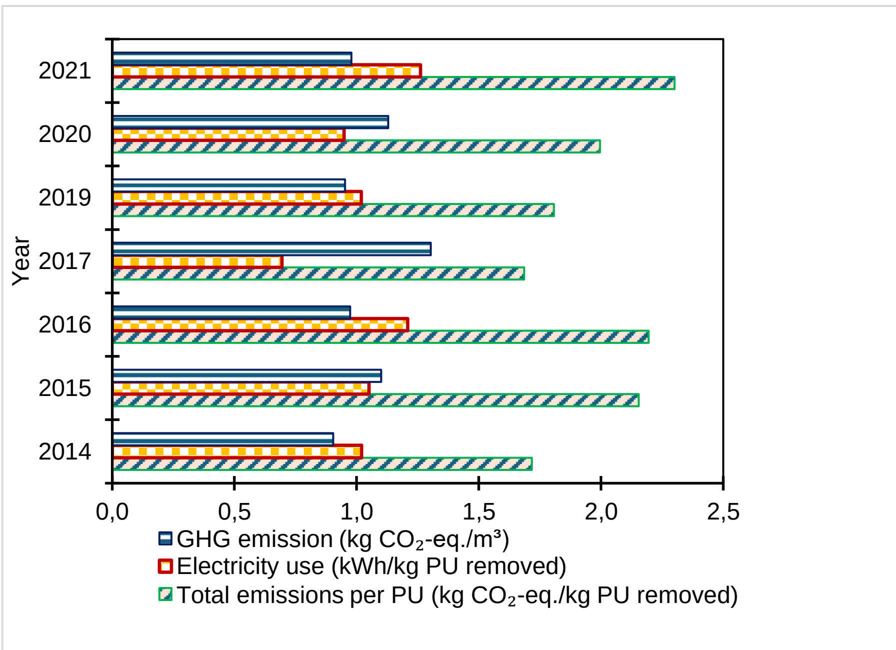

Figure 3. Efficiency indicators related to GHG emissions, electricity use, and emissions intensity per pollution unit.

Although total GHG emissions were highest, the efficiency indicators suggest a lower (more efficient) emissions intensity per PU removed. Electricity use was most efficient in 2017, aligning with the high TE, resulting in lower emissions intensity per PU removed. Higher values in 2021 stem from poor TE. Conversely, the deficiency of volumetric indicators (Longo et al., 2016) of TE reflects the undesirable high value of the emissions per cubic influent in 2017.

6.3.5.3 Comparison with previous studies

This study found onsite emissions to be 82.27% and offsite emissions 17.73%, consistent with claims that water and sludge treatment accounts for 23–83% of WWTP GHG emissions (Wu et al., 2022; Kyung et al., 2015). In contrast, offsite emissions from electricity consumption had the highest influence in other studies (Chen, 2019; Tong et al., 2024; Zhou et al., 2022). The CH_4 and N_2O from treatment processes and CO_2 from electricity consumption constituted 66.56%, 2.42%, and 13.65% of the total emissions, respectively, aligning with findings (Zhou et al., 2022) where CH_4 contributed the most. In other studies, CO_2 from electricity consumption (Masuda et al., 2015) and N_2O (Kyung et al., 2015; Parravicini et al., 2016) were key contributors. Previous studies on the assessment of municipal (Keller and Hartley, 2003; Kyung et al., 2015) and industrial (Bani Shahabadi et al., 2010) WWTPs obtained emission intensities of 2.5, 2.81-3.75, and 10.6 kg CO_2-eq./kg BOD, respectively, compared to 9.49 kg CO_2-eq./kg BOD, in this study. The values from (Kyung et al., 2015) are similar to our research. However, varied emission intensities can be influenced by treatment technology, capacity, influent quality, and water quality objectives (Zhou et al., 2022).

Discrepancies among studies stem from estimation methods and system boundaries. This study applied the IPCC method. Masuda et al. (2015) employed onsite gas sampling, and (Kyung et al., 2015) developed a model. Moreover, our study applied the IPCC Tier 1 conditions due to data limitations, which assigns a singular emission factor to all wastewater and sludge treatment processes. Other studies used country, process (Kyung et al., 2015), and season (Yapıcıoğlu and Demir, 2021) specific emission factors. Additionally, our study considered CO_2 (including biogenic), CH_4, and N_2O, while others did not consider biogenic CO_2 (Zhou et al., 2022) and N_2O (Bani Shahabadi et al., 2010; Keller and Hartley, 2003). The GWP values used were inconsistent. This study used the latest IPCC (IPCC, 2014) 100-year GWP values for CH_4 and N_2O as 28 and 265, respectively. Despite previous criticism of the methodology for emission overestimation (Wang et al., 2022), this study followed the IPCC guidelines, the prevailing standard in the field.

6.3.5.4 Implications for WWTP Operations

6.3.5.4.1 Pollutant removal

The variability in pollutant TE, especially for NO_3-N, FCC, and BOD, underscores challenges in meeting standards consistently, warranting further investigation into influencing factors. Compliance relies on precise monitoring and treatment parameter adjustments. The consistently good WWQI reflects effective overall water quality maintenance, contrasting with EQI variations indicating specific pollutant removal needs, especially in response to seasonal and annual changes. The WWTP demonstrates robust COD, BOD, and TSS removal exceeding 90%, attributed to advanced biological and sedimentation techniques. High coliform removal suggests stable microbial treatment processes. Stable microbial removal indicates reliable biological treatment, possibly due to well-functioning aeration tanks or reactors. Fluctuations in pH and DO removal may stem from operational conditions such as disruptions in aeration linked to chemical imbalances, warranting closer examination. Seasonal nutrient removal variations highlight the need for a nuanced understanding of nutrient dynamics and implementing targeted strategies to optimise removal.

Ultimately, high positive loadings suppose high TE, reflecting WWTP performance. The fluctuations in PCs correspond to changes in factors such as temperature, precipitation, operational process, lifestyle, and living standards (Li et al., 2021; Platikanov et al., 2014), affecting runoff and pollutant loads during the rainy season (Platikanov et al., 2014). The PCs illustrate the interrelation of water quality parameters in the treatment process. The interdependence between the removal of organic matter, suspended solids, and faecal coliform is implied, where one could reflect the removal of the other (Seo et al., 2019). The concentration of Fe^{2+} substantially affects coliform removal in wastewater (Aguilar-Ascon, 2019; Ibrahim et al., 2019), while the elimination of sulphate, NO_3-N, NO_2-N, and NH_4-N is enhanced in certain anaerobic (Zhao et al., 2006; Qin et al., 2021) and aerobic processes (Assefa et al., 2019). Sulphur-based autotrophic denitrification impacts NO_3-N and potentially NO_2-N (Bezbaruah and Zhang, 2003). Maintaining a pH between 6.4 and 7.2 improves phosphorus removal (Liu et al., 2007). Ion exchange aids in NO_3-N and Cl^- removal, supported by conventional coagulants like ferric chloride (Ratnayaka et al., 2009; Aghapour et al., 2016). Therefore, continuous monitoring, routine maintenance, and adherence to operational best practices ensure WWTP stability and the production of high-quality effluent. Addressing issues highlighted by yearly variations requires a targeted approach, emphasising the need for a comprehensive operational strategy that considers seasonal influences and potential challenges in maintaining treatment performance.

6.3.5.4.2 Mitigation of GHG emissions at the WWTP

Various strategies are recommended for reducing GHG emissions at WWTPs. Integration of CO_2 capture, storage, and valorisation can significantly reduce emissions (Kyung et al., 2015). The implementation of CH_4 capture during sludge treatment and utilising CH_4 generated by anaerobic processes can mitigate onsite emissions, especially by substituting CH_4 for fossil fuel consumption (Bani Shahabadi et al., 2010; Kyung et al., 2015). Renewable technologies like small hydro and photovoltaic systems offer potential solutions (Tong et al., 2024). The incorporation of advanced biological technologies, maximising anaerobic organic matter removal, microalgae utilisation (Campos et al., 2016) and employing anammox processes for ammonia removal (Tong et al., 2024) are crucial in next-generation WWTP designs for GHG emission minimisation (Campos et al., 2016) The optimisation of DO and COD/N ratio in the nitrification and denitrification stages can mitigate N_2O emissions (Kyung et al., 2015), since aeration is the most prominent source of offsite GHG emissions from electricity consumption (Kyung et al., 2020, 2015). It implies that emissions can be decreased by optimising electricity consumption for aeration (Campos et al., 2016) without compromising TE (Kyung et al., 2015).

Moreover, it is essential to find an optimal SRT for the simultaneous reduction of CO_2 and N_2O emissions (Campos et al., 2016). The goal is to operate at the shortest SRT possible to reduce CO_2 emissions while allowing sufficient time for microorganisms to consume N_2O emissions without compromising effluent quality (Campos et al., 2016). Ultimately, deploying IoT technology in innovative and intelligent management systems for possible remote control and optimised operation of aeration, pumping, and dosing units increases energy efficiency (Tong et al., 2024).

6.4 Limitations

The deficiency of data might have impacted the results of this study. Data gaps exist for several parameters from 2019 to 2021, including TCC, NO_2-N, SO_4, Fe^{2+}, and Cl^-. Administrative issues at the WWTP caused the unavailability of the 2018 dataset. Additionally, data on total nitrogen, phosphorus, and solids were missing. Sludge generation was estimated based on total suspended solids, neglecting total dissolved solids. This oversight may have led to underestimating sludge generation, affecting CH_4 emissions and chemical usage in sludge treatment. Total nitrogen estimation based on NH_4-N, NO_3-N, and NO_2-N might result in underestimation, as these components account for less than 50% of TN. The use of PO_4 instead of total phosphorus impacts EQI estimations. Both local (e.g., NESREA) and international standards were used to assess compliance, though NESREA regulations were prioritised, affecting compliance assessments. Subsequently, FCC was monitored using the maximum permissible limits for E. coli.

Secondly, the correlation matrix computed with pairwise deletion maximised available data, unlike listwise deletion, which reduces sample size and information loss. Pairwise deletion retains more cases for analysis but may yield varying sample sizes across analyses, affecting comparability. In PCA analysis, missing data points were filled with parameter averages, potentially masking data extremes. This approach may imply dataset homogeneity, inaccurately representing the true diversity and variability of the parameters. In the PCA analysis, the missing data points were filled up automatically with the average of the respective parameter. Filling missing values with averages may diminish the impact of outliers on the analysis, potentially overlooking important data extremes. As a result, the study may inadvertently convey a sense of homogeneity in the dataset that does not accurately represent the true diversity and variability of the variables. Again, GHG emission values may, in reality, exceed those obtained in this study. Average inflow and outflow values for rainy and dry seasons were used, yet, increasing connections to sewers and population growth suggest rising flow trends.

Furthermore, the operational complexity of the WWTP, characterised by irregular aggregate use, poses significant challenges. It is exacerbated by inadequate electricity supply, leading to considerations of electricity demand throughout the study. Optimising energy consumption, including load balancing and operational adjustments, is crucial to address electricity demand challenges. However, intermittent aggregate operation complicates energy and TE assessment, hindering the identification of stable operating conditions and optimisation opportunities. Throughout the study, electricity consumption rate was linked to influent flow, but this assumption challenges energy dynamics assessment. Onsite factors like diesel quality can impact electricity generation efficiency, necessitating advanced modelling and optimisation strategies for accurate outcomes.

6.5 Conclusion

This study provides valuable information on WWTP operations in a typical urban African city based on statistical analysis of water quality parameters, indices, and the quantification of onsite and offsite GHG emissions. Most effluent quality parameters consistently complied with the standards, except NO_3-N, FCC, and BOD. The maximum TE of 97.41%, 96.26%, 91.63%, and 91.05% were connected to TCC, FCC, TSS, and BOD, respectively. This high efficiency was likely due to increased oxygenation. The TE varied with seasons, with that of pH, SO_4, and COD higher in the dry season and DO, NH_4-N, PO_4, and FCC higher in the rainy season. Sustainable measures are needed for increased and consistent removal of NO_3-N, FCC, and BOD. The WWQI incorporates more parameters than EQI and is potentially more decisive. Their average values were 343,058.59 kg/month and 39.08, respectively. The EQI indicated a significantly higher effluent quality in the dry season, while WWQI suggested better quality in the rainy season. The WWQI indicates potential harm if discharged into surface water bodies without further treatment. Multivariate analyses revealed critical relationships among parameters, aiding the simultaneous removal of contaminants and formulation of numerical models to predict performance.

The primary sources of GHG emissions were recognised and quantified. Various mitigation measures for GHG emissions were enumerated. Average GHG emissions from the WWTP was 7,270.8 t CO_2-eq./yr, with wastewater and sludge treatment responsible for over 80%. Methane constituted a more significant portion (68.15%) of GHG emissions. The electricity consumption rate of the WWTP was estimated as 10,192.15 kWh/d, resulting in a GHG emission rate of 2,734.97 kg CO_2 eq./d. Electricity use accounted for 77.44% and 13.73 % of offsite and total GHG emissions, respectively. Optimisation of onsite wastewater treatment processes, such as the aeration basins, can significantly reduce GHG emissions. This study provides practical knowledge into GHG emissions from WWTPs using activated sludge processes in developing countries, though emissions per unit process were not considered. An energy audit is recommended to understand the WWTP's performance better. Further examination of cradle-to-grave environmental impacts using the life cycle assessment approach is essential. A robust data collection regime on energy use and water quality changes at the unit process level promises more precise outcomes. This study forms a foundation for computing the contribution of the water sector to the national GHG emission data in Nigeria, applicable in low- and middle-income countries.

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7. Environmental and Economic Assessment of Electricity Recovery Technologies at a Wastewater Treatment Plant in Abuja, Nigeria.

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Abstract

Local energy recovery with WWTPs is expected to reduce energy consumption while promoting energy self-sufficiency. In this study, energy recovery technologies for electricity generation are presented to determine their environmental and economic status for a WWTP in Abuja, Nigeria. Anaerobic digestion (AD), Incineration (INC), and Hydroelectric (HEP) technologies were examined. The environmental assessment was achieved using the life cycle assessment method with six impact categories: climate change, photochemical ozone creation potential (POCP), and acidification potential (AP). The economic feasibility was determined using the net present value (NPV), life cycle cost, levelized cost of energy (LCOE), annualised cost, payback period, and internal rate of return (IRR). The generation of 809-3862 t thickened sludge per annum presented a methane yield of 3.1-14.9 x 10^3 m^3/year with an electricity generation potential of 6.5-31.4 MWh/year. Also, the electricity generation potential for HEP and INC was 30.9-147.5 and 19.9-95 MWh/year. HEP has insignificant environmental impacts. Global warming potential was 4.9-23.2 and 9.2-43.8 t CO_2 eq./yr for AD and INC, respectively. POCP was 3.62-17.3 and 1944.49-9282.03 kg NMOVC eq./yr for AD and INC, respectively. Also, AP was 1.84-8.79 mol H+ eq./yr AD and 1406.94 - 6716.02 mol H+ eq./yr for INC. NO_x and CH_4 were gas-to-air emissions with the most considerable environmental impacts. The economic metrics indicated that AD was the most valuable, with a positive NPV, IRR >10%, and LCOE of 0.11 USD/kWh. HEP had the highest NPV and an LCOE of 0.22-0.33 USD/kWh. The NPV was 2.4-17.9 x 10^5, 8.3-79.4 x 10^4, and 1.1-7.9 x 10^5 USD for HEP, INC, and AD, respectively. INC present the least desirable economic value. Integration of two or more of these technologies in the future may provide more desirable economic and environmental benefits. This study offered technical insights to potential investors, policymakers, and non-

profit organisations intending to catalyse investments in energy recovery technologies in the water industry.

Keywords: Waste-to-energy; Cost Benefit; Greenhouse Gases; Emissions Simulation; Energy Independence.

7.1 Introduction

Population expansion, economic growth, and inadequate water and sanitation infrastructure in low- and lower-middle-income countries, especially in Africa, have led to a critical rise in pollution exposure (UNEP, 2016; WWAP, 2017). WWTPs are vital contributors to pollution control and public and environmental health protection. However, operating within strict discharge standards implies the application of chemicals, resources, and energy. These facilities have high energy demand, predominantly from fossil origins in most developed countries (Li et al., 2021; UNEP, 2016; WWAP, 2017). These operating conditions have economic and environmental consequences.

Energy costs are the most expensive factor in operating WWTPs in developed and developing countries (Montwedi et al., 2021). The total energy usage in WWTPs comprises 60-90% of electricity consumption, while energy consumption cost represents 20-40% of the operation costs (Sun et al., 2019). Wastewater treatment constitutes about 3-5% of overall electricity consumption globally (Power et al., 2014). It takes-up over 50% of energy use in the South African water sector, while water supply and wastewater systems comprise 25% of Urban energy consumption (Montwedi et al., 2021). In the United States, the production and distribution of potable water and wastewater collection and treatment use 4% of total electricity demand (Longo et al., 2016). In parts of Europe, demand from WWTPs accounts for 1% of national electricity consumption (Longo et al., 2016). The annual carbon footprint of WWTPs ranges from 7-108 kg CO_2eq/pe, influenced primarily by Scope 1 and 2 emissions in the Nordics (Power et al., 2014). About 0.25% of national energy consumption in China relates to WWTPs (Sun et al., 2019).

Moreover, low-and-middle-income countries spend up to 1 billion USD annually from official development assistance on WWTPs, yet they are not or partially functional (WaterAid, 2020). Erratic power supply and mismanagement of sludge are the major challenges facing WWTPs in developing countries (World Bank Group, 2017). Similarly, water treatment facilities in Nigeria are going comatose mainly due to energy and operation costs (FMWR et al., 2022; Solihu & Bilewu, 2021). Dwindling economic resources led to reduced allocation from the government for public utilities. Ageing infrastructure and limited technical expertise also contribute to the high O&M cost (World Bank, 2021b). Most WWTPs are conventional and mechanical types that consume high energy. Unfortunately, they rely heavily on diesel generators, which are expensive to run (FMWR et al., 2022; Solihu & Bilewu, 2021). Besides, about 60 million Nigerians own generators and spend over N3.5 trillion on fuel and O&M costs. The generator importation in Nigeria is one of the highest in the world, valued at N151 billion (Ayodele & Ogunjuyigbe, 2015). Cases of accidents and deaths due to fume poisoning from diesel generators have been reported. Hence, there is an increased dialogue and drive for integrating Renewable Energy Sources into the country's electricity mix (Ayodele & Ogunjuyigbe, 2015). The Nigerian government launched a plan to increase the renewable energy in the energy mix to 36% by 2030. The Renewable Energy Master Plan was intended to promote energy security and regulate the carbon footprint of the country's energy sector (ITA, 2021). The power sector has an installed capacity of about 12,522 MW. However, the total quarterly available generation decreased by 18.06% (NERC, 2022b) in Q2 of 2022, regarding 9,480.21 GWh in Q4 2021 (NERC, 2022a). Unfortunately, several incidents of grid collapse have been reported - 2 each in Q1 and Q2 2022 (NERC, 2022b, 2022a), 17 in 2017 (Premium Times, 2023), 130 between 2013-2022 (The Guardian, 2022) and 206 between 2010-2019 (The Cable, 2019).

Improved sustainability in the industry depends primarily on renewable energy generation and energy use optimisation (Power et al., 2014). Reducing electricity consumption in the water industry has been a matter of growing interest in recent years (Bousquet et al., 2017). It is attainable by onsite generation for use or connected to the grid (Bousquet et al., 2017). There is a possibility to recovery energy through methane from anaerobic digestion of sludge, sludge incineration, and hydropower using wastewater flow. It is achievable without affecting the functioning of the WWTP (Bauer et al., 2017; Bousquet et al., 2017; Power et al., 2014).

Previous studies highlighted the challenges and opportunities of energy self-sufficiency of WWTP with AD of sewage sludge in developed countries (Shen et al., 2015). Several commercial biogas plants run solely on sewage sludge; for example, a plant at Veolia's subsidiary in Sofia produces 2.4 MWh/yr electricity for powering plant operations. Biogas from domestic sewage provides 45,000 MWh/yr of electricity in Dubai (Meladi, 2019) and 3.8 MWh/yr of electricity and heating used in facility operations in Serbia (MET Group, 2021). Likewise, two biogas plants in Oregon, USA, generate 6,000 MWh/yr and 4,324 MWh/yr for electricity and heating purposes (Clackamas County, 2018; Hayward, 2018; Loggan, 2021). Also, an integrated biogas plant in Gamasa, Egypt, produces about 1,396.5 kWh of electricity to supplement the WWTP needs (Awad et al., 2019).

Anaerobic digestion and incineration of wastewater sludge for energy recovery are relatively recognised globally (Nkuna et al., 2024; Power et al., 2014) with a life span of up to 25 and 37 years, respectively (Bakkaloglu & Hawkes, 2024;

Benato et al., 2022; Tangri, 2023). It contributes over 90% to the renewable energy recovered in the UK water sector (Power et al., 2014). INC showed lower energy deficit and costs than AD and could offer a sustainable sludge management option (Hao et al., 2020). An AD-INC outperformed an INC system regarding energy efficiency and GHG emissions from sludge treatment at high organic content. However, a lower organic content favoured the INC system (R. Chen et al., 2022). Energy utilisation of INC was below 28% when waste heat was underutilised. The environmental footprint of coal and gas was 100 times that of sludge (Liu et al., 2023). Co-incineration of sludge could reduce investment costs up to 2-4 times (Liu et al., 2023). Moreover, pollutant emission, agglomeration, and sintering are major problems faced in the INC of sewage sludge (Hu et al., 2021).

The concept of hydropower generation in wastewater infrastructure is still evolving (Power et al., 2014). A framework for estimating hydropower potential in WWTPs with limited data was developed in South Africa (Bekker et al., 2022). Hydropower has been integrated into water and wastewater infrastructure in Switzerland, Korea (Bauer et al., 2017; Bousquet et al., 2017; Llácer-Iglesias et al., 2021), UK (Power et al., 2014), and South Africa (Bekker et al., 2022). The footprint of conventional hydropower is estimated as 23-24 (Ubierna et al., 2022) compared to 2.1 gCO_2-eq/kWh (Bauer et al., 2017) from integrated HEP. HEP uses minimal concrete and steel, representing about 70% of total GHG emissions (Bauer et al., 2017). It does not require a water diversion dam or flooding of land by a reservoir (Bousquet et al., 2017) and has a lifespan of up to 70 years (Bauer et al., 2017). The impact of the operation phase of both hydro systems on climate change is negligible. In comparison, nuclear and wind power have lesser lifecycle GHG emissions of about 12 gCO_2-eq/kWh. While solar, gas, and coal have a value of 48, 490 and 820 gCO_2-eq/kWh, respectively (Ubierna et al., 2022).

Waste streams from municipal solid waste (MSW) and wastewater have provided sources for energy recovery. In Nigeria, energy recovery potential from MSW has been significantly explored using several waste-to-energy (WtE) technologies. The AD had the highest energy generation (Lagos (683 kWh/t) and Abuja (667 kWh/t)) compared to INC and LFGTE (Nubi et al., 2022). Landfills in Adamawa states could generate 15 Gg/yr of MSW and release 0.31 Gg/yr of LFG, producing 33.78 GWh of heat or 10.14 GWh of electricity (Usman, 2022). AD of abattoir waste showed the potential to produce 1.03 l/day of biogas, generating 1,040 MWh of electricity (Odekanle et al., 2020). The organic fraction of MSW in selected Nigerian cities was projected to generate 4.74 × 109 kWh of electricity from 669 Gg of methane due to 36,250 Gg of waste in 2030 (Yusuf et al., 2019). In Ibadan, Ayodele et al. (2018) estimated the mean electricity generation as

321.73-652.15 GWh for AD and 63.25-436.18 GWh for LGTE for 20 years. Other studies showed a combustible 14 million tonnes of waste worth about 4.4 TWh of electricity (Akhator et al., 2016). Atta et al. (2016) estimated that a population of 158 million would generate 40 million tons of MSW, producing 3,000 MW of electricity. Ogunjuyigbe et al. (2017) performed a comparative analysis of hybrid WtE systems.

However, the water and wastewater sectors are underexplored. Ogbu et al. (2023) evaluated the energy potential of centrally collected sewage sludge at regional locations. The wastewater and sludge generated from households were assessed based on population, water access, and sewer connection. The AD technology was the most technically viable, with a maximum generation of 6.8 GWh/yr in the North Central. In comparison, the INC outperformed AD in most financial viability indicators. Additionally, previous works highlighted the hydropower potential energy in Nigeria and its position in driving the power sector (Eweka et al., 2022; Ugwu et al., 2022). Integration of HEP into existing infrastructures such as WWTPs, flood control dams, water reservoirs, and irrigation networks was emphasised (Ugwu et al., 2022).

Furthermore, these energy recovery techniques (i.e., AD, INC, and HEP) are understudied for decentralised energy applications in the Nigerian water industry. There has been little research estimating their potential at any WWTP in Nigeria. Hence, this study aims to (i) Estimate the potential of energy recovery from three technologies, namely, AD, INC, and HEP, at a WWTP; (ii) Provide an environmental and environmental assessment of these technologies; (iii) Offer a comparison of the technologies to establish the appropriate technological strategy. The economic and environmental analysis is expected to provide background knowledge for policymakers and shareholders in the Nigerian renewable energy and water sectors.

7.2. Methodology

7.2.1 Study location

The Wupa WWTP is in the Idu Industrial area of Abuja, Nigeria. It lies between latitudes 70' 201" and 90' 201"N and longitudes 60' 451" and 70' 391"E close to the Wupa River (Francis & Ndububa, 2022). The WWTP is an activated sludge process type (Balogun & Ogwueleka, 2021) comprising mechanical and biological processes. It operates below its design capacity of 131,250 m^3/day and is powered by diesel generators. It was intended to serve a population of 700,000 and expandable to 1,000,000. The pretreatment stage involves the screw pumps, screens, grit, and scum removal. The secondary stage consists of the aeration basins, clarifiers, and the UV channel, the tertiary phase. Waste sludge is passed through the gravity thickener, the filter belt dewatering system, and the final mass is sent to the drying lagoon. The temperature in the area ranges from 27°C to 36°C with a mean value of 29°C (Balogun & Ogwueleka, 2021). Abuja is in Nigeria's central region, with the most significant rainfall from April to October and a minimum from November to March (World Bank, 2021a). Datasets on mean values of monthly inflow (m^3/d), influent and effluent water quality were obtained from the Wupa WWTP.

7.2.2 Characterisation of sewage sludge

The total solids (TS) and moisture content (MC) were determined by the gravimetric method based on Rice et al. (2017) as described in Velkushanova et al. (2021). The elemental analysis (Carbon, Hydrogen, Nitrogen, Sulphur and Oxygen) of the sewage sludge was obtained through a CHNSO Analyzer (Thermo Finnigan, Italy; FLASH EA 1112 series). The calorific value (gross calorific value or higher heating value: HHV) was determined by using a calorimeter IKA 6000 (IKA-Werke GmbH & Co. KG, Staufen, Germany) according to (BS EN ISO 18125, 2017). About 1 g of the analytical sample compressed in an unbreakable test piece was placed into the calorimeter, which was set up with information such as sample weight, hydrogen content (H), etc. Then the net calorific value or lower heating value: LHV (MJ/kg) was calculated using eqn. (1). All trials had been carried out in triplicates.

$$\mathrm{LHV} = \mathrm{HHV} - 2.44(9 \times \%\mathrm{H} + \%\mathrm{MC}) \quad (1)$$

7.2.3 Estimation of WW flow and sludge generation

According to mass balance by Piao et al. (2016), 99.95-99.99% of inflow reaches the discharge point. Therefore, the outflow (m^3/d) is given as:

$$\mathrm{Q_{out}} = \mathrm{Q_{in}} \times 0.9997 \quad (2)$$

It is assumed that sludge is from secondary treatment alone because primary sedimentation at the WWTP is absent. Therefore, secondary sludge flowing to the gravity thickener is equivalent to influent TS ($\mathrm{TS_{in}}$) ($\mathrm{kg\ TS\ influent/d}$). Secondary sludge flow (m^3/d) is given as:

$$\mathrm{SSW} = \frac{\mathrm{TS_{in}}}{\frac{\mathrm{Dry\ solids(\%)}}{100} \times \mathrm{sludge\ density}} \quad (3)$$

For secondary sludge, dry solids = 0.6-1%, density =1,001 kg/m^3 (Andreoli et al., 2007).

Thickened effluent sludge (sludge to be sent to the dewatering) represented by the thickened TS effluent load (kg TS/d) is given as:

$$TS_{T\_eff} = \text{Solids capture} \times \Delta TS \tag{4}$$

$$\Delta TS = TS_{in} - TS_{out} \tag{5}$$

The thickened sludge flow (m^3/d) going to dewatering is estimated by:

$$TSW = \frac{TS_{T\_eff}}{\frac{\text{Dry solids(\%)}}{100} \times \text{sludge density}} \tag{6}$$

For thickened sludge, dry solids = 2-7%, density = 1,003-1,010 kg/m^3 (Andreoli et al., 2007). ΔTS (kg TS/d) is the influent load; TS_{out} (kg TS effluent/d) is the mass of effluent TS. Solid capture for gravity thickening = 75-85% (Andreoli et al., 2007).

Dewatered sludge production (sludge for final disposal) derived as the dewatered TS effluent load (kg TS/d) is expressed as:

$$TS_{D\_eff} = \text{Solids capture} \times TS_{T\_eff} \tag{7}$$

The dewatered sludge (m^3/d) sent for final disposal is estimated by:

$$DSW = \frac{TS_{D\_eff}}{\frac{\text{Dry solids(\%)}}{100} \times \text{sludge density}} \tag{8}$$

For dewatered sludge, dry solids = 20-40%, density = 1,050-1,100 kg/m^3. Solids capture for dewatering by filter belt press = 90-98 % (Andreoli et al., 2007).

7.2.4 Estimation of energy recovery potential of proposed technologies

7.2.4.1 Anaerobic digestion technology for energy recovery from sewage sludge

The theoretical potential volume (m^3/t) of biogas production from the AD of organic matter is determined using the Buswell equation (Amoo & Fagbenle, 2013; Ogunjuyigbe et al., 2017; Salami et al., 2011):

$$C_nH_aO_bN_c + (n - 0.25a - 0.5b + 0.75c)H_2O \rightarrow (0.5n - 0.125a + 0.25b + 0.375c)CO_2 + (0.5n + 0.125a - 0.25b - 0.375c)CH_4 + cNH_3 \tag{9}$$

The values of the variables n, a, b, and c are determined by normalised mole ratio (Ogunjuyigbe et al., 2017) given as:

$$\text{Mole Ratio} = \frac{K[C,H,O,N]}{M[C,H,O,N]} \tag{10}$$

Where, K is the elemental composition (C, H, O, N) derived from the ultimate analysis of sewage sludge (Singh et al., 2020); M = molar mass of the elements, C = 12.01 g, H = 1.01 g, O = 16 g, and N = 14.01 g (Nubi et al., 2022).

The mass, kg/t of methane (M_{CH_4}) and carbon dioxide (M_{CO_2}) produced from AD is given by:

$$M_{CH_4} = \frac{16 \times A_1}{(M_C \times n) + (M_H \times a) + (M_O \times b) + M_N} \times 1{,}000 \quad (11)$$

$$M_{CO_2} = \frac{44 \times A_2}{(M_C \times n) + (M_H \times a) + (M_O \times b) + M_N} \times 1{,}000 \quad (12)$$

$$A_1 = 0.5n + 0.125a - 0.25b - 0.375c \quad (13)$$

$$A_2 = 0.5n - 0.125a + 0.25b + 0.375c \quad (14)$$

The volume of methane (m^3/t), $V_{CH_4} = \frac{M_{CH_4}}{\rho_{CH_4}}$ (15)

The volume of carbon dioxide (m^3/t), $V_{CO_2} = \frac{M_{CO_2}}{\rho_{CO_2}}$ (16)

Where, ρ_{CH_4} and ρ_{CO_2} are densities of methane (0.717 kg/m^3) and carbon dioxide (1.938 kg/m^3) (Ogunjuyigbe et al., 2017).

The actual volume of methane produced during the AD process is less than the theoretical volume and is expressed as 85% of the theoretical volume of methane. The actual volume of methane and carbon dioxide is taken as (Salami et al., 2011):

$$V_{CH_4(Actual)} = \frac{V_{CH_4} \times 85}{100} \quad (17)$$

$$V_{CO_2(Actual)} = \frac{V_{CO_2} \times 85}{100} \quad (18)$$

The electrical energy (kWh) from AD is given by:

$$E_{AD} = \frac{MSWS_{AD} \times V_{CH_4(Actual)} \times LHV_{CH_4} \times CF \times \eta_{AD}}{3.6} \quad (19)$$

Where, $MSWS_{AD}$ is the mass of sewage sludge (in tonnes) for the AD process obtained from eqn. (4); LHV_{CH_4}= lower heating value of methane, 37.2 MJ/m^3 (Nubi et al., 2022); η_{AD} is the efficiency of the AD technology, 0.30 (Singh et al., 2020); 3.6 is the conversion factor from MJ to kWh.

The size (kW) of a proposed technology based on the estimated electrical energy is determined using:

$$P_{S(i)} = \frac{E_{(i)}}{8{,}760 \times CF_{(i)}} \quad (20)$$

Where, where 8,760 is the number of hours of plant operation per annum; E_i and CF_i are the electrical energy (kWh) and a capacity factor of the ith technology, i.e., AD, INC, or HEP. The CF for AD, INC, and HEP is 68%, 68%, and 58% (IRENA, 2023).

7.2.4.2 Incineration Technology for energy recovery from sewage sludge

Electrical energy (kWh) from the INC technology is calculated as:

$$E_{INC} = \frac{LHV_{DSWS} \times MSWS_{INC} \times CF \times \eta_{INC}}{3.6} \tag{21}$$

Where, LHV_{DSWS} is the lower heating value of dried sewage sludge. $MSWS_{INC}$ is the total mass of dried sewage sludge (in tonnes) processed for INC obtained from eqn. (7). η_{INC} = electrical efficiency of the INC technology, taken as 20% (Nubi et al., 2022).

7.2.4.3 Hydroelectric Technology for energy recovery from effluent flow

The total hydroelectric energy (kWh) from the HEP technology is calculated as (Bekker et al., 2022; Ugwu et al., 2022):

$$E_{HEP} = \eta \times \rho \times g \times H \times Q_{out} \times 8{,}760 \times CF \tag{22}$$

Where, η = system efficiency, ρ = water density (1,000 kg/m^3), g = gravitational acceleration (9.8 m/s2), H = available head (m), and Q = outflow of the WWTW (m^3/s). According to Bekker et al. (2022), when H is unknown, three heights can be assumed: Low head of 1 m, a medium head of 3 m and a high head of 5 m. In this study, H = 3 m is assumed.

7.2.4.4 Diesel displacement by equivalent alternative energy

The annual diesel consumption saved (L/yr) using a proposed technology rather than the combustion of diesel fuel can be calculated using (Ayodele & Ogunjuyigbe, 2015):

$$F_{d(i)} = \left(0.246P_{S(i)} + 0.08415P_G\right) \times 8{,}760 \tag{23}$$

7.2.5 Environmental Assessment

The goal of LCA in this paper is to evaluate the emission potentials by using effluent flow and sludge from WWTP for electricity production by applying AD, INC, and HEP technologies at the WWTP. The amounts of fossil fuel (Diesel) that could be displaced using these alternative electricity sources are also studied. The functional unit is the electricity generated per volume of influent wastewater (Q_{in}) treated yearly. The Q_{in} generates sludge (TS_{T_eff}) and effluent (Q_{out}). The effluent is directed towards HEP and sludge to AD or INC, as shown in Figure 1.

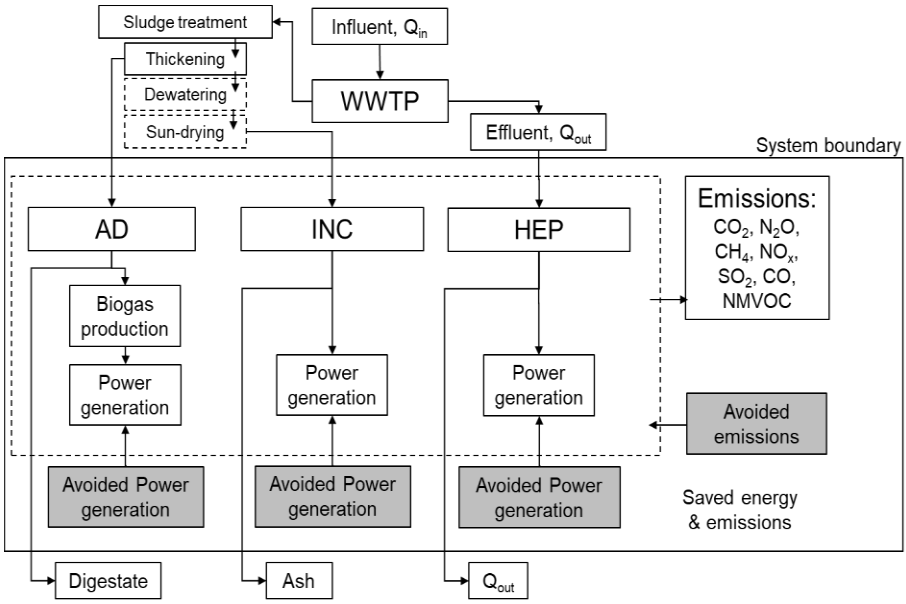

Figure 1. System boundary of study.

System Boundaries: The treatment of influent wastewater results in sludge generation. The system boundary of the study starts at the point where sludge and effluent are released. All technologies share the WWTP operation; hence, it is not included. Also, sludge thickening and dewatering were not considered because they are part of the baseline operation of the WWTP. Processes analysed include sludge input, electricity production, and aerial emissions.

Life cycle inventory: The LCI data were obtained from the WWTP, IPCC guideline (IPCC, 2002, 2006), and US EPA compilations (EPA, 2020, 2023, 2024). Aerial emissions are often categorised into air pollutants, organic pollutants, greenhouse gases (GHGs), acidic gases, and heavy metals (Ayodele et al., 2017). The emissions included in this study are shown in Figure 1. The PEF method based on EF Reference Package 3.1 (European Commission, 2023) was used specifically the characterisation factors for emissions to air. The six impact categories considered include Acidification potential (AP), Climate Change (indicated by GWP), Freshwater Ecotoxicity (FET), Human toxicity (non-cancer) (HTCn), Particulate matter (PM), and Photochemical ozone creation potential (POCP).

Assumptions: All environmental impacts generated from producing a product before becoming waste were neglected. Only the operation phase of the technologies was considered. Therefore, energy and emissions during construction and decommissioning of the WtE technologies were not considered.

All technologies were located on the WWTP site at an equal distance from the residue disposal site. Therefore, emission due to residue transportation for AD and INC was ignored because the emission in each case was the same. Emissions due to residue disposal, i.e. ash from incineration and digestate from AD, were unaccounted for.

7.2.5.1 Evaluation of gas to air emission from the scenarios

The gaseous emissions are estimated by multiplying the activity data by the emission factors. The activity data are described in terms of the mass or energy value of feedstock. The emission factors of the various gases under consideration are shown in Table 1.

Table 1. Emission factor of gas to air emissions.

		Emission Factors [b, m, n, p]		
S/N	Aerial Emissions	INC	AD (kg/TJ)	Diesel (kg/TJ)
1	CH_4	300 [*, n]	5 [n]	10 [m]
2	CO_2	100,000 [*, n]	54,600 [n]	74,100 [m]
3	N_2O	4 [*, n]	0.1 [n]	0.6 [m]
4	SO_2	0.277 [**, q]	2.792 [q]	347.22 [p]
5	NO_x	2.5 [**, b]	100 [^, m]	5,222.22 [p]
6	CO	15.5 [**, b]	50 [^, m]	1,127.78 [p]
7	NMVOC	600 [*, m]	5 [^, m]	5 [m]

[*]Units in kg/TJ; [**]Units in kg/tonne. [^]Value for natural gas adopted. Sources: [a](IPCC, 2014); [b](EPA, 2023); [n](IPCC, 2006); [m](IPCC, 2002); [p](EPA, 2020); [q](Ayodele et al., 2017)

7.2.5.1.1 Incineration Technology

The mass of gaseous emissions from the combustion of sludge is given by:

$$E_{(g)_{INC}} = EF_{(g)} \times M_{F_{INC}} \tag{24}$$

Where, g represents the associated gases shown in Table 1 (i.e. g=1 means CH_4, g=2 means CO_2, g=3 means N_2O etc). $EF_{(g)}$ is emission factor for g.

7.2.5.1.2 Anaerobic digestion plant

The primary source of CH_4 emission in AD facilities is leakages, which amount to about 5% of biomethane produced (IPCC, 2006). Emissions from the digestion plant and the combustion of CH_4 are considered here. Emissions of CH_4 and CO_2 during digestion are given by eqn. (25) and (26).

$$E_{CH_{4_{Digestion}}} = 0.05 \times V_{CH_{4_{Actual}}} \times \rho_{CH_4} \times M_{F_{AD}} \tag{25}$$

$$E_{CO_{2_{Digestion}}} = GWP_{CO_2} \times V_{CO_{2_{Actual}}} \times \rho_{CO_2} \times M_{F_{AD}} \tag{26}$$

The mass of gaseous emissions from the combustion of methane is given by:

$$E_{(g)_{Combustion}} = EF_{(g)} \times E_{AD} \tag{27}$$

Where, g represents the associated gases shown in Table 1 (i.e. g=1 means CH_4, g=2 means CO_2, g=3 means N_2O etc). $EF_{(g)}$ is emission factor for g.

7.2.5.1.3 Avoided Emissions

The emissions in kg per year that could be prevented using a proposed technology rather than the combustion of diesel fuel can be calculated using:

$$E_{F_{d(i)}} = F_{d(i)} \times EF_{(g)} \tag{28}$$

7.2.5.2 Evaluation of environmental impact potentials

The impact of each technology is quantified by multiplying the mass of emission by the characterisation factor. The impact categories, associated emissions and corresponding characterisation factors are shown in Table 2.

Table 2. Characterisation (equivalency) factor of gas to air emissions.

Emissions	GWP	HTCn	POCP	FET	AP	PM
CH_4 (biogenic)	29.8	6.2186E-08	0.0101	0.32011	-	-
CH_4 (fossil)	29.8	5.0095E-08	1	8.6069	-	-
NMVOC (biogenic)	29.8	1.1026E-07	1	9.4933	-	-
NMVOC (fossil)	29.8	1.1026E-07	1	9.4933	-	-
CO_2 (biogenic)	1	-	-	-	-	-
CO_2 (fossil)	1	-	-	-	-	-
N_2O	273	1.6045E-08	-	-	-	-
CO (biogenic)	-	0	-	0.022837	-	-
CO (fossil)	-	0	0.0456	0.022833	-	-
NO_x	-	-	1	-	0.74	1.6E-06
SO_2	-	-	0.0811	-	1.31	0.000008

Source: (European Commission, 2023)

$$EI_{(i)} = CF_{(i)} \times E_{(g)} \tag{29}$$

Where, $EI_{(i)}$ is the impact category, i, $CF_{(i)}$ is the characterisation factor of $EI_{(i)}$, $E_{(g)}$ is the mass of gaseous emission.

7.2.6 Economic Analysis of Energy Recovery Technologies

The parameters considered for economic analysis include Life Cycle Cost (LCC), Net Present Value (NPV), Investment cost, Operation and Maintenace (O&M) Cost, Levelized Cost of Energy (LCOE), Payback Period (PBP), Annualised Cost (AC), and Internal Rate of Return (IRR).

7.2.6.2 Life Cycle Cost (LCC)

The LCC (in USD) in eqn. (29) (Ogunjuyigbe et al., 2017) is the sum of all expenses incurred throughout the ownership and operation of a project.

$$LCC = C_{inv(i)} + \sum_{n=1}^{N} \frac{C_{O\&M(i)}}{(1+d_n)^n} \quad (30)$$

Where $C_{inv(i)}$ is the initial cost of the investment (in USD); $C_{O\&M(i)}$ is the cost of O&M (in USD); d_n is the nominal discount rate (%); N is the project's lifespan in years.

7.2.6.3 Net Present Value (NPV)

The NPV (in USD) is the total present value of all the system's lifetime expenses minus the total current value of all its revenues. For viable projects, NPV>0. NPV is calculated as (Ogunjuyigbe et al., 2017):

$$NPV = \sum_{n=0}^{N} \frac{F_n}{(1+d_r)^n} = F_0 + \frac{F_1}{(1+d_r)^1} + \frac{F_2}{(1+d_r)^2} + \ldots\ldots\ldots + \frac{F_N}{(1+d_r)^N} \quad (31)$$

Where, F_n is the net cash flow rate (USD); d_r is the annual real discount rate.

$$F_n = R_{(i)} - C_{inv(i)} - C_{O\&M(i)} \quad (32)$$

$$R_{(i)} = E_{(i)} \times F_e \quad (33)$$

$$d_r = \left(\frac{1+d_n}{1+e}\right) - 1 \quad (34)$$

Where, $R_{(i)}$ is the revenue accrued from the energy recovery project (in USD); $E_{(i)}$ stands for Total Electrical Energy from each technology (kWh); F_e is the sale price of electricity in Nigeria, taken as 0.132 USD/kWh (NERC, 2024); i is the technology of interest, i.e., HEP, INC or AD; e is the inflation rate as defined by the Central Bank of Nigeria, taken as 28.92% (CBN, 2023).

7.2.6.1 Investment and O&M Costs

Anaerobic Digestion Technology

The cost model (USD) (Hadidi & Omer, 2017) for $C_{inv(AD)}$ and $C_{O\&M(AD)}$ is presented as:

$$C_{inv(AD)} = C_{P_{(AD)}} \times P_{s_{AD}} \quad (35)$$

$$C_{O\&M(AD)} = 0.03C_{inv(AD)} + 0.005E_{AD} \quad (36)$$

Where, $C_{P_{(AD)}}$ the value of the plant-specific cost for AD plants is USD 4,339/kW.

Incineration Technology

The cost (USD) model (Nubi et al., 2022) for $C_{inv(INC)}$ and $C_{O\&M(INC)}$ is given as:

$$C_{inv(INC)} = 16{,}587 \times (P_{S(INC)})^{0.82} \quad (37)$$

$$C_{O\&M(INC)} = 0.04 \times C_{inv(INC)} \quad (38)$$

Hydroelectric Technology

The project cost, USD, for hydroelectric power installed at WWTP is given as (Power et al., 2014):

$$C_{inv(HEP)} = 1.26075 \times \left[25{,}000 \times \left(\frac{P_{S(HEP)}}{H^{0.35}}\right)^{0.65}\right] \text{; For H < 30 m} \quad (39)$$

Where, 1.26075 is the current GBP to USD exchange rate according to IMF (2024).

$$C_{O\&M(HEP)} = 0.03 \times C_{inv(HEP)} \quad (40)$$

7.2.6.4 Levelized Cost of Energy (LCOE)

The lowest selling price of the produced electricity is calculated from the LCOE in USD/kWh. Equation (26) can be used to determine the LCOE for each technology (Ogunjuyigbe et al., 2017):

$$LCOE_{(i)} = \frac{LCC_{(i)}}{E_{p_{(i)}}} \times CRF_{(i)} \quad (41)$$

$$CRF = \frac{d_n(1+d_n)^N}{(1+d_n)^N - 1} \quad (42)$$

Where, CRF is the capital recovery factor.

7.2.6.5 Annualised Cost (AC)

A project's annualised cost (USD/yr) is the cost that results in the exact net present cost as the actual cash flow sequence associated with that project if it occurs evenly every year of the project's existence. It is calculated as (Heaps, 2022):

$$AC = (CRF \times C_{inv}) + C_{O\&M} \quad (43)$$

7.2.6.6 Pay Back Period (PBP)

It is the period (years) during which the costs of a project are recovered. It is calculated using:

$$PBP_{(i)} = \frac{LCC_{(i)}\ (USD)}{R_{(i)}\ (USD/year)} \quad (44)$$

7.2.6.7 Internal Rate of Return (IRR)

It is approximately the maximum discount rate at which the project breaks even. The technology is viable when NPV>0 and the IRR is at its highest level (Nubi et al., 2022).

IRR (%) = the value of d_r such that $\mathrm{NPV} = \sum_{n=0}^{N} \frac{F_n}{(1+d_r)^n}$ (45)

7.2.6.8 Cost of Fuel Saved

The cost of diesel fuel that could be saved per annum using a proposed technology rather than the combustion of diesel fuel can be calculated as (Ayodele & Ogunjuyigbe, 2015):

$$C_{F_{d(i)}} = F_{d(i)} \times C_d \tag{46}$$

Where, C_d is the current price of diesel, taken as 0.78 USD/l (NBS, 2024).

7.3. Results and Discussion

The energy recovery potential, environmental impact, and economic assessment using different technologies at the selected WWTP are discussed in this section. The analysis is based on two scenarios: when the treatment plant operates at the current condition - base case (BC); and when operating at design conditions - full capacity (FC). In the full capacity scenario, only the influent flow rate, m^3/d, changes and is used to estimate the outflow and sludge generation. Operational data from the WWTP used in relevant analyses are shown in Appendix D.

7.3.1 Wastewater and sludge characteristics

The characteristics of the sewage sludge from the WWTP are shown in Table 3. The carbon content was 9.03±0.03%. Ash content and Volatile solids were 76.27±1.49% and 23.73±1.49%, respectively.

Table 3. Characteristics of sewage sludge.

Parameter	Value (%)
C	9.03±0.03
H	2.15±0.36
N	1.00±0.01
S	0.12±0.01
O	11.43±1.20
VS	23.73±1.49
Ash	76.27±1.49
Moisture content	31.43±0.13
Total solids (TS)	68.57±0.13

The HHV and LHV of the sewage sludge dry matter were 3.55 and 2.31 MJ/kg, respectively. The energy value is low, probably because the sludge has been partially decomposed and deposited on the drying bed. Moreover, the sludge treatment line has been out of operation for a while before the sludge sampling regime. The treatment line operates for about 60-70 days annually. Similar energy values of 1.5-2.75 MJ/kg were obtained in China (Xiao et al., 2022). The low energy value of sludge was linked to a high content of inorganic materials such as sand and dust (Twagirayezu et al., 2024). These materials enter the collection system either in systems that use combined drainage for wastewater and rainwater (Twagirayezu et al., 2024) or through breakages/cracks in the network. However, authorities recommend that biomass with an energy value of 6.25 MJ/kg (EPA, 2013) or 6 MJ/kg (World Bank, 1999) are suitable as bioenergy resources. Although the sludge analysed in the study falls below this range, collecting sludge at proper points and age at the WWTP could improve these values (Singh et al., 2020). Moreover, other studies obtained higher values. In Europe, the HHV of sludge varied from 12.7-15.5 MJ/kg dried basis (Bianchini et al., 2015) in Italy to 20.43 MJ/kg (at 6.2% moisture content) in France. The HHV was also reported as 18.75 MJ/kg in Canada (Z. Chen et al., 2014) and 8-21 MJ/kg (Singh et al., 2020) in India. At the same time, an LHV of 9-12 GJ/ton (at 90% dry matter content) was recorded in Turkey (Ozcan et al., 2015).

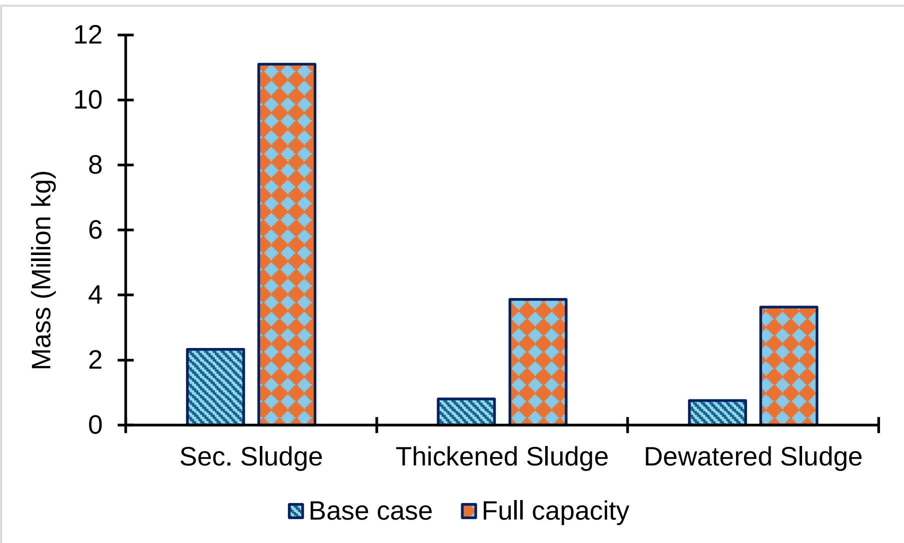

Figure 2. Annual Sewage sludge generation potential of WWTP and different operational capacities.

When operating under actual and design conditions, the effluent outflow at the WWTP was estimated as 27,487.33 and 131,210.63 m^3/d, respectively. The quantity of sludge generated along different stages is represented in Figure 2.

At the current operating conditions, the generation potential of secondary sludge was 2,326.32 t/yr containing 0.8% dry solids, thickened sludge was 809.05 t/yr with 4.5% dry solids while the dewatered sludge was 760.51 t/yr with 30% dry solids. However, at design capacity, the secondary sludge, thickened sludge, and dewatered sludge could potentially amount to 11,104.67, 3,862, and 3,630.28 t/yr, respectively. Final dried sludge is reported to contain between 80-90% dry solids. The values obtained are slightly comparable to the reports of an annual generation of 547.2 tons (Francis & Ndububa, 2022). In this study, the effluent flow is dedicated towards recovery energy by HEP, while the sludge generation is used to estimate the potential from INC and AD.

7.3.2 Energy Recovery Potential

The electrical energy recovery potential at the WWTP using the proposed technologies is presented in Figure 3.

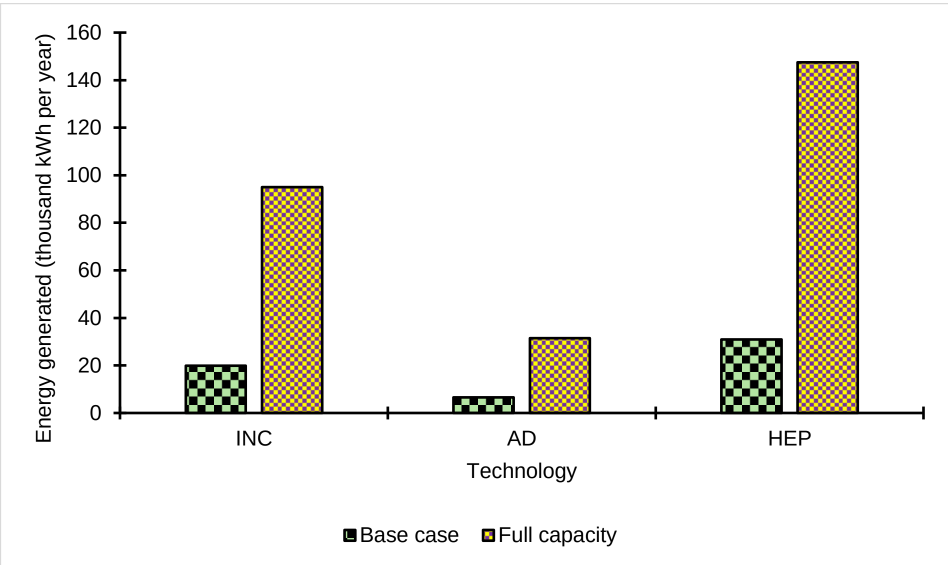

Figure 3. Annual electrical energy recovery potential by proposed technologies.

Capacities and benefits, such as diesel fuel saved for the selected technologies for each scenario, are shown in Table 3. In the current conditions, about 30,889.56 kWh per year could be generated at the WWTP from HEP. Similarly, 19,910.1 kWh per year could be generated from INC and 6,585 kWh per year from AD. The energy recovered from HEP, INC, and AD can displace over 8.98 x 10^5, 8.92

x 10^5, and 8.86 x 10^5 litres of diesel per year. In comparison, the increase in energy generation and diesel savings at full capacity of the WWTP is shown in Figure 3 and Table 4, respectively.

The results show that the electricity generation potential of INC and AD are about 64.4% and 21.32% of HEP, respectively. In comparison, that of AD is 33.1% of INC. HEP outperforms other technologies in BC and FC scenarios due to its inherent advantages, such as consistent water flow and high energy conversion efficiency. The continuous flow of wastewater provides a reliable energy source to power the HEP, resulting in higher energy recovery potential compared to INC and AD, which are highly dependent on the VS content of solids in the wastewater.

Table 4. Sizes and benefits of energy recovery technologies.

Technology	Base case		Full capacity	
	Power (kW)	Fuel saved (litres/year)	Power (kW)	Fuel saved (litres/year)
INC	3.34	891,781.34	15.94	918,937.42
AD	1.11	886,967.01	5.28	895,956.27
HEP	6.08	897,686.23	29.02	947,124.41

Moreover, the low VM-ash ratio of the sludge adversely affects the potential of INC, while the C/N ratio influences biogas production. Both INC and AD show substantial increases in energy recovery potential at FC compared to BC, reflecting the scalability of these technologies with increased wastewater processing capacity. However, HEP maintains its dominance in energy generation even at full capacity, underlining its resilience and efficiency. Moreover, the CH_4 and CO_2 generation from AD were 3,122.94-14,907.32 and 2,289.62-10,929.46 m^3/year, respectively.

7.3.3 Environmental Impacts

HEP systems have insignificant operational emissions (Bauer et al., 2017); therefore, a zero-emission profile in all accessed impact categories is attributed to HEP in the current study. The climate change potential indicated by GWP, kg CO_2eq./yr for each scenario is shown in Figure 4. The INC emissions were highest in both scenarios. It is because of the increase in sludge generation in the plant when it operates at full capacity. The GWP for BC and FC scenarios was 9,168.27 and 43,764.67 kg CO_2 eq./yr, respectively. In contrast, lower values were observed in AD with 3,571.5 and 17,012.5 kg CO_2 eq./yr, respectively. The results were primarily influenced by CO_2 and CH_4 for INC and AD, respectively. In INC, 78.2% of the GWP was attributed to CO_2 emissions. In AD, CH_4 leakage accounted for 68.6%, while biogas production accounted for over 73.2% of GWP. Biogenic CO_2 was considered in these analyses. Similar values were reported previously, with AD having higher CH_4 emissions, INC had more N2O emissions, while CO_2 was disregarded (Twagirayezu et al., 2024).

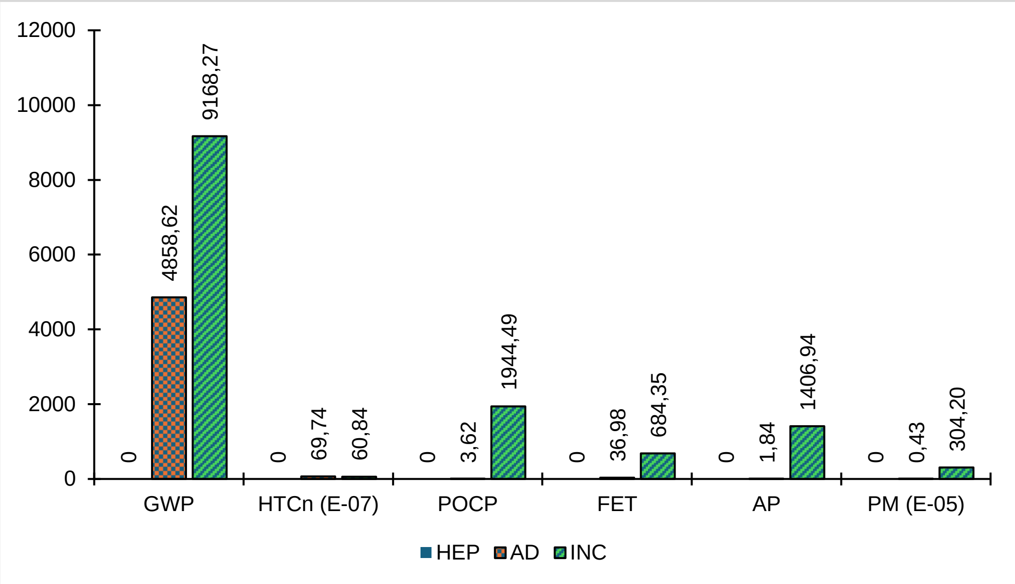

Figure 4. Environmental impacts of energy generation from proposed technologies.

POCP expresses the potential of ozone creation by the photochemical oxidation of volatile organic compounds, CO, in the presence of NO_x and sunlight. High accumulations of tropospheric ozone cause damage to vegetation and human respiratory systems (Zampori & Pant, 2019). The estimated POCP expressed as kg NMVOC eq./yr for each scenario is shown in Figure 4. In this study, CH_4, NO_x, CO, SO_2, and NMOVC emissions to air are considered. The lowest POCP was observed in AD with 3.62 and 17.3 kg NMOVC eq./yr values for BC and FC scenarios, respectively. In comparison, INC had the highest POCP in both scenarios, with 1944.49 and 9282.03 kg NMOVC eq./yr, respectively. NO_x accounted for over 97% of POCP from INC, while NO_x and CH_4 contributed 65.4% and 31.2% from AD.

AP is the conversion of air pollutants (e.g. NO_x, SO_2, and NH_3) into acidic substances (Assamoi & Lawryshyn, 2012). These substances can cause acidic rain (Ayodele et al., 2017). A principal consequence of air acidification is the decline of lakes and forests (Assamoi & Lawryshyn, 2012). In this study, AP accounts for the NO_x and SO_2 emissions. The INC performed poorly from an environmental perspective compared to the AD regarding AP. The estimated AP expressed as mol H+ eq./yr for each scenario is shown in Figure 4. The AD outperformed INC from an environmental perspective in terms of AP. The lowest AP was observed in AD with values 1.84 and 8.79 mol H+ eq./yr for BC and FC scenarios, respectively. While INC had the highest AP in both scenarios with 1,406.94 and 6,716.02 mol H+ eq./yr, respectively. NO_x accounted for 99.9% and 95.3% of AP from INC and AD, respectively.

FET explains the toxic effects caused by the release of certain compounds, which damage species and change the structure and function of an ecosystem (Zampori & Pant, 2019). Emissions of CH_4, NMVOC, and CO were considered for FET. The estimated FET expressed as CTUe/yr for each scenario is shown in Figure 4. The lowest values of 36.98 and 176.55 CTUe/yr were obtained in AD for both BC and FC scenarios, respectively. In comparison, INC had higher POCP values in both scenarios, with 684.35 and 3,266. CTUe/yr, respectively. CH_4 and NMOVC were the main contributors from AD and INC, respectively. NMOVC and CO contributed 59.7% and 39.3% of FET from INC, respectively. At the same time, CH_4 and NMVOC accounted for 96.9% and 3% of FET from AD, respectively.

HTC accounts for the adverse health effects on humans caused by the intake of toxic compounds through inhalation, food/water consumption, and skin penetration (Zampori & Pant, 2019). In this study, Human toxicity - non-cancer (HTCn) was more prominent regarding air emissions considered and hence emphasised. HTCn impacts are not caused by particulate matter/respiratory inorganics or ionising radiation. The estimated HTCn expressed as CTuh/yr for each scenario is shown in Figure 4. The toxicity potential of AD is marginally higher than INC in both scenarios. It is linked to the estimated volume of biogas leakage in AD. Emissions of CH_4, N_2O, and NMVOC were considered for HTCn. CH_4 and NMOVC were the main contributors from AD and INC, respectively. About 99.8% and 22% were attributed to CH_4, while NMVOC accounted for 0.2% and 77.9% of HTCn from AD and INC, respectively.

PM addresses the adverse human health impacts caused by emissions of particulate matter and its precursors (NO_x, SO_x, NH_3) (Zampori & Pant, 2019). Emissions of NO_x and SO_x were considered for a PM. The estimated PM for each scenario is shown in Figure 4. INC produced a higher PM than AD across all scenarios. The lowest PM was observed in AD with values 4.32×10^{-6} and 2.06×10^{-5} for BC and FC scenarios, respectively. Higher PM was observed in INC with values 3.04×10^{-3} and 1.45×10^{-2} for both scenarios. Emissions of NO_x accounted for 99.9% and 87.8% of PM from INC and AD, respectively.

Implication of Environmental Impacts

Diesel is used to fuel the automobile engines for power generators at the WWTP. The combustion of diesel releases GHG and other air pollutants in the environment. The use of the proposed alternative energy sources can displace diesel generators. The environmental impacts avoided are shown in Figure 5.

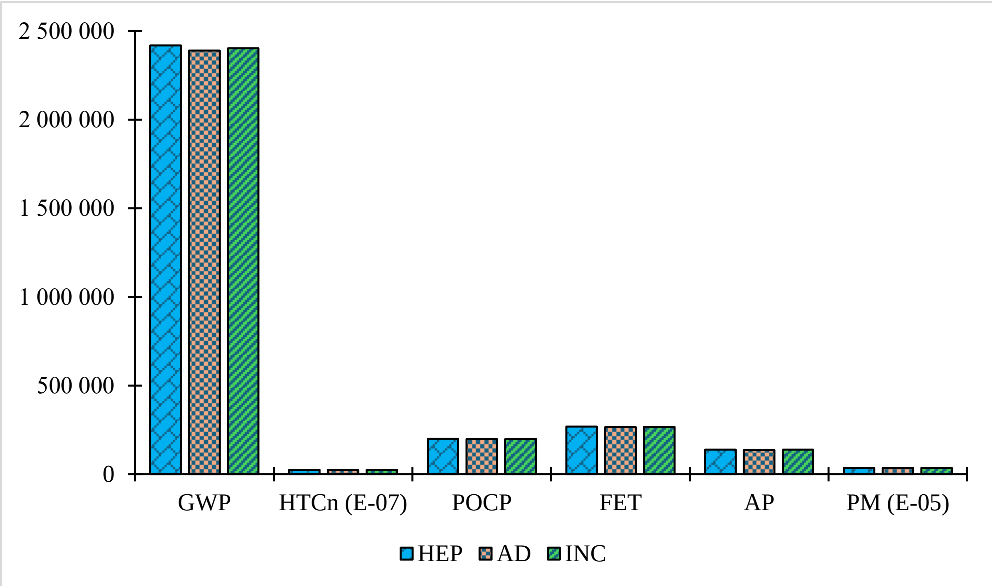

Figure 5. Environmental impacts of diesel avoided by using the energy recovery technologies.

The difference in this value among the technological options is not very substantial. However, HEP has the highest value, followed by INC and AD. As expected, the values are directly proportional to their estimated energy recovery potential.

The proposed technologies are assumed to produce energy to displace emissions from diesel generations. Regarding avoided emissions, i.e., environmental offsets, HEP is best, and AD outperforms INC in all but GWP. HEP systems have negligible operational emissions, contributing to their zero-emission profile across all environmental impact categories (Bauer et al., 2017). Environmental impacts associated with HEP, primarily from the construction and operation of dams, including habitat alteration, biodiversity loss, and upstream flooding, are inapplicable in this case since they are integrated into already existing infrastructure (Bauer et al., 2017; Bousquet et al., 2017).

Moreover, based on emission per kWh, AD outperformed INC in all impact categories except climate change and HTCn. While INC may have advantages in specific impact categories, such as human toxicity and climate change, its overall environmental performance per kWh remains inferior to AD. Effective biogas capture and utilisation strategies are essential to mitigate methane emissions in anaerobic digestion systems. Implementing biogas recovery systems, gas-tight covers, and proper system design can help minimise biogas leakage and maximise methane utilisation for energy generation (Ijoma et al., 2022; Mills et al., 2014). Additionally, enhancing digester operation and management practices, such as optimising organic loading rates and maintaining optimal temperature and pH conditions, can improve biogas production efficiency and reduce emissions (Ijoma et al., 2022; Nkuna et al., 2024).

NO_x is the most important contributor to environmental impacts influencing acidification, photochemical ozone creation, and respiratory health issues. CH_4 is a potent GHG emission with a higher GWP than CO_2. The emission of CH_4 from biogas leakage constitutes a primary environmental concern, contributing significantly to the overall GWP. Conversely, the GWP of INC is primarily influenced by CO_2 during combustion. The higher values of AP and POCP in INC align with a previous study (Mills et al., 2014) that suggested that exhaust emissions (including CO, NO_x, SO_2 and VOCs) have a significant influence on AP and POCP than lower direct emissions from biogas production. However, the amount of NO_x and SO_2 emissions from INC is correlated with the Nitrogen and Sulphur content of sludge (Assamoi & Lawryshyn, 2012). These pollutants are emitted at much higher intensities from incineration than AD. Potential emission sources during the sludge INC process include heavy metals, gas pollutants, hydrofluorocarbon, and residue (slag and fly ash) (Nkuna et al., 2024). Factors such as waste composition, operating conditions, and emission control measures influence the magnitude of emissions from INC (Hu et al., 2021). NO_x emissions can be mitigated by implementing advanced combustion technologies and air pollution control systems. Techniques such as selective catalytic reduction and flue gas desulfurisation can effectively curtail NO_x and SO_x emissions, respectively (Nkuna et al., 2024; Twagirayezu et al., 2024). Furthermore, optimising combustion processes, controlling combustion temperature, and implementing efficient air-fuel mixing can help minimise pollutant creation with increased efficiency (Nkuna et al., 2024; Twagirayezu et al., 2024).

7.3.4 Economic Assessment

The economic viability of the proposed technologies is demonstrated in Table 5. They are assessed based on five indicators ((NPV, LCC, LCOE, IRR, PBP, and ACS). The shading in the cells shows comparisons between the rows per indicator per scenario. The light and dark shades indicate the lowest and highest values, respectively, as shown at the root of the table.

In the base scenario, the AD has an NPV of 108,525.84 USD, an LCC of 6,021.69 USD, an IRR of 14%, and an LCOE of 0.11 USD/kWh. The annualised cost is 707.31 USD/year and a PBP of about 7 years. The AD presents the lowest LCC, LCOE, ACS, and PBP and the highest IRR. However, its NPV is lower than that of HEP but higher than that of INC. Therefore, AD is most attractive and competitive due to low costs and high returns. On the other hand, HEP has the best NPV of 239,562.81 USD. The IRR, LCOE, and PBP of HEP are better compared to INC.

However, HEP has the highest values of LCC and ACS compared to AD and INC. While HEP has competitive returns, high costs make it unattractive. On the other hand, INC has the lowest NPV, IRR, and PBP, in addition to the highest LCOE. The negative IRR values for INC and HEP imply a likely loss on the investment. Nonetheless, the IRR, LCOE, and PBP for AD remained constant at full capacity. NPV, LCC and ACS increase to 517,556.77 USD, 28,744.51 USD, and 3,376.32 USD/year, respectively. The AD presents the lowest LCC, LCOE, ACS, and PBP and the highest IRR. Its NPV is the lowest yet profitable. Hence, AD remains most preferred based on economic metrics. The HEP has the best NPV of 239,562.81 USD. Its IRR, LCOE, and PBP were all improved and better than in INC. However, the LCC and ACS remain the highest compared to AD and INC. Hence, HEP remains unappealing due to costs. Although all INC metrics improved, the LCOE, IRR, and PBP were undesirable. The LCC and ACS were better than in HEP, while the NPV was better than in AD. Furthermore, HEP had the highest cost savings due to diesel displacement, while AD had the least. It is anticipated since the quantity of diesel displaced is directly proportional to the generation capacity of the system.

Table 5. Economic feasibility indicators of proposed technologies for electricity production.

Tech	NPV (USD)	LCC (USD)	IRR (%)	LCOE (USD/kWh)	ACS (USD/year)	PBP (year)	$C_{F_{d(i)}}$ (USD)
Base Case							
INC	82,867.08	59,768.12	-8	0.36	7,020.34	22.99	695,589.44
AD	108,525.84	6,021.69	14	0.11	707.31	6.92	691,834.27
HEP	239,562.81	87,787.86	-5	0.33	10,311.53	21.51	700,195.26
Full Capacity							
INC	794,479.21	215,335.39	-2	0.27	25,293.21	17.17	716,771.19
AD	518,047.43	28,744.51	14	0.11	3,376.32	6.92	698,845.89
HEP	1,794,961.51	275,152.70	2	0.22	32,319.33	14.13	738,757.04

	Lowest		Highest

Economic implications

The capital and O&M costs were highest for HEP and lowest for AD. The capital cost, O&M cost, and revenue attributes are also displayed in Figure 6. It indicates that AD requires the least initial investment compared to HEP. However, HEP generates the highest benefits in terms of avoiding the cost of diesel or revenue from electricity tariffs. It is reflected in its best NPV across all scenarios, which indicates its profitability as an investment over time.

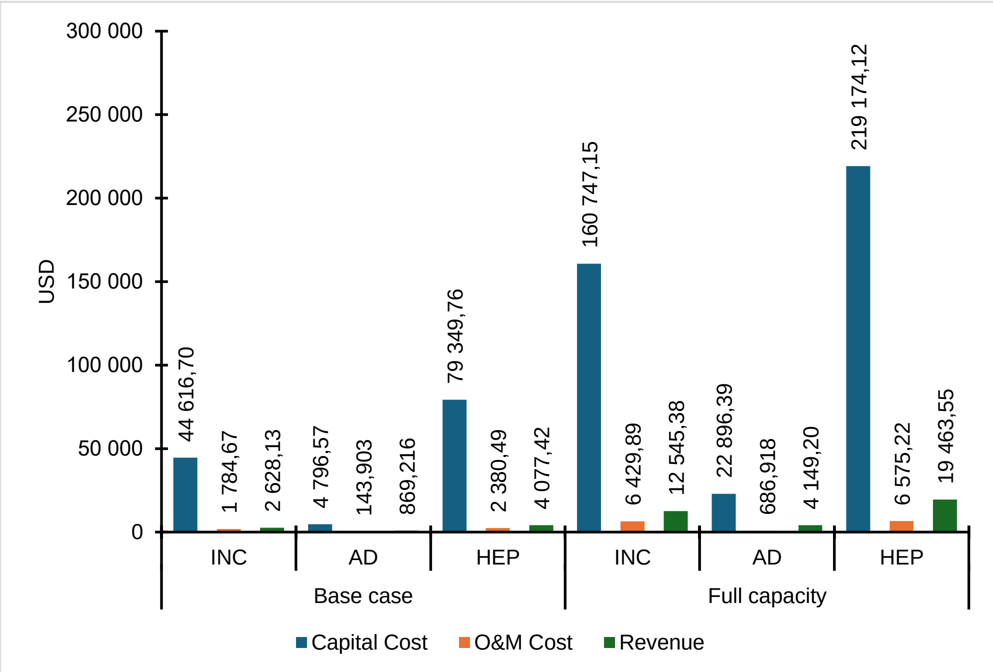

Figure 6. Capital cost, O&M cost, and revenue of proposed technologies for electricity production.

However, AD has the best IRR, unlike HEP. IRR indicates economic feasibility. Previous studies have recommended IRR > 10%. Only the AD, among other technologies, meets this requirement. Moreover, the lower cost and higher return make AD superior, and even the NPV for AD remains viable. The production of a unit of electricity is the cheapest for AD, as reflected in its LCOE. However, HEP and INC have comparable electricity production costs. It is a likely decisive factor in the selection of technology. For economic feasibility, previous studies recommended a PBP of 7 years for WtE technologies (Mabalane et al., 2021; Nubi et al., 2022) and 10 years (Power et al., 2014) for HEP. However, other HEP studies applied a baseline of 25 years in their assessment (Bousquet et al., 2017). The AD has a PBP of about 7 years, 18-23 years for INC, and 15-22 years for HEP. AD meets the benchmark, while HEP barely meets the upper limit.

In other studies (Ogbu et al., 2023) on WtE using sewage sludge in Nigeria, the INC rated better than AD in four (LCC, LCOE, IRR, and ACS) out of six economic indicators. However, the two indicators (NPV and PBP), which AD rated highly, were crucial. AD was desirable in a similar study in Colombia due to the higher IRR, although LCOE was higher (Alzate-Arias et al., 2018). AD was preferred for MSW management in Nigeria due to superior NPV, LCOE, and PBP (Ogunjuyigbe et al., 2017). In contrast, INC was more viable for MSW (Nubi et al., 2022) with desirable LCC, LCOE, IRR, NPV, and shorter PBP. INC was preferred over AD for WtE from MSW in UAE (Abdallah et al., 2018) and Oman (Abushammala & Qazi, 2021). In the UAE, INC had a better IRR and a lower LCOE (Abdallah et al., 2018). However, AD had better PBP and IRR in Oman, but INC was chosen based on higher NPV and lower LCOE (Abushammala & Qazi, 2021). Nonetheless, INC was often favoured because of combustibles such as plastics, which had higher energy value. At the same time, AD utilised only the organic fraction, which was less in quantity and energy value. INC showed better metrics in other studies (Ogbu et al., 2023). Therefore, centralised co-incineration with sludge from other WWTPs or MSW could make it more viable. On the other hand, its noteworthy that HEP has a life span twice as AD and INC (Bakkaloglu & Hawkes, 2024; Bauer et al., 2017; Benato et al., 2022; Tangri, 2023), which might afford just enough time to recoup initial investments.

7.3.5 Discussion

The technical, environmental, and economic analyses in this study have demonstrated that HEP and AD emerge as competitive energy recovery technologies for WWTPs. The renewable energy sources assessed in this study present a substantial economic advantage and low emissions compared to diesel fuel-powered generators. The WWTP has an estimated energy need of 3,720,134.75 kWh per year (i.e. 10,192.15 kWh/d). Investing in these renewable energy technologies appears unjustifiable compared to growing energy needs. However, their environmental profile and cost savings (especially fuel cost) make them attractive.

The HEP had negligible operational emissions, while construction impacts were significantly reduced since fewer materials are required to integrate them into existing structures at WWTPs. AD proved moderate efficiency and promising environmental and economic performance, making it a sustainable and cost-effective option for electricity generation. Moreover, the digestate from AD is suitable for soil conditioners and fertiliser – a potential economic benefit. However, its electricity generation capacity is the lowest amongst others. Both technologies offer competitive economic indicators and contribute to sustainable development goals by reducing greenhouse gas emissions and promoting renewable energy generation.

Although INC showed undesirable economic and environmental concerns, it had a high energy recovery potential. Additionally, other studies have shown INC to be promising. INC could be more energetically balanced than AD when considering electrical and thermal energy recovery (Hao et al., 2020). Moreover, recovered heat can be further used in sludge drying or urban heating/cooling. INC implementation is declining in the UK due to high O&M costs (Mills et al., 2014). However, Hao et al. (2020) argue that onsite biogas production is more feasible than INC when the WWTP is not connected to the grid, eliminating the cost of cable connection and fixed cost of electricity. Previous studies have also highlighted how economic metrics analysed in this study are influenced by changes in factors such as sludge generation rate, wastewater flow rate, electricity generation efficiency, electricity tariff, plant capacity factor, discount rate, capital and O&M cost, and population growth rate (Ayodele et al., 2018; Ogbu et al., 2023).

Furthermore, INC could be preferred over AD due to its lesser space requirement and ability to reduce the initial sludge volume by 90 % (Twagirayezu et al., 2024). Small-scale INCs are economically inefficient but can be optimised by co-incineration with MSW or other solid fuels (Liu et al., 2023; Nkuna et al., 2024). Hence, centralised facilities make solid economic gains for INC. Additionally, sewage sludge is a biomass, and biogenic emissions are considered neutral by IPCC guidelines (IPCC, 2006), although it might contain heavy metals and inorganic pollutants. The INC of sewage sludge generates lower emissions than diesel and other fossil fuels. Meanwhile, according to Liu et al. (2023), the energy recovered offsets these emissions since it is a waste management technique. However, INCs are also disadvantaged by expensive emission control systems, high ash production, and potential discharge of toxic substances (Hu et al., 2021; Nkuna et al., 2024).

Key factors affecting the energy generation of these technologies include electricity generation efficiency, plant capacity factor, and feedstock (wastewater/sludge) availability (Ayodele et al., 2018). The high efficiency (60-80%) (Bekker et al., 2022) of micro hydro systems is credited to converting the kinetic energy of flowing water into mechanical energy, which is then converted into electrical energy through turbines and generators. However, INC and AD generally have lower efficiencies of 30% and 20% (Singh et al., 2020), respectively, compared to HEP. The efficiency of incineration is influenced by factors such as the calorific value of the waste feedstock, combustion temperature, and efficiency of heat recovery systems. Critical parameters of the INC system include air distribution, feed ratio, flow rate, and resident time (Nkuna et al., 2024). In comparison, AD processes involve the biological breakdown of organic matter by anaerobic microorganisms to produce biogas, which is then used to generate electricity or heat.

Sludge characteristics also influence energy recovery. Higher moisture can lead to irrecoverable heat loss during combustion through evaporation due to reduced temperature and lower heat transfer efficiency (Nkuna et al., 2024). Efficient energy recovery requires sludge MC below 40% (R. Chen et al., 2022). High ash and MC levels can also lead to slag formation and reactor blockage in thermochemical operations (Gao et al., 2020). Meanwhile, carbon content is directly proportional to lower heating value (LHV), while sulphur content indicates the formation of SO_x, particulates, and acid deposition. Elevated sulphur content can inhibit potassium silicate development, decreasing bed agglomeration (Nkuna et al., 2024). The efficiency of AD depends on sludge characteristics (moisture content, C/N ratio, TS/VS) and operational procedures, temperature control, and retention time (Nkuna et al., 2024). Consequently, the typical focus on AD in developed countries arises from the higher VS content in sewage sludge than in developing countries. Comparable to the present study, VS content ranges from 30-50% in developing countries to 60-70% in developed countries (Twagirayezu et al., 2024).

Sludge drying is also a significant factor in sludge management. It could consume much more energy than produced by INC. However, increasing VS and use of renewable energy could offset energy consumption in drying (Twagirayezu et al., 2024). Drying lessens the amount of sludge and, invariably, the cost of handling and conveyancing sludge. The use of free solar energy in drying could minimise operational costs. However, the efficiency of trying systems depends on drying time, geographical location, and sludge origin/characteristics. (Bennamoun, 2012)

Uncertainties and limitations accompany the data and assumptions made in this study. The infrequent operation of the sludge treatment unit at the WWTP affected the proper sampling of sludge, which invariably influences the recovery potential of INC and AD. Operating the HEP at a head below 2-3 m could diminish its viability in energy generation and economics, and this head was adopted from literature due to a lack of onsite data. Effluent discharge data was also unavailable. Certain cost components such as transportation, labour, and taxes were ignored, which might not provide an accurate picture. Lastly, the emission and characterisation factors used might have underlying limitations.

In the future, onsite pilot studies of the technologies with long-term measurements will provide compelling data for a robust comparison since the potential is now evident. Expanding the system boundary to include onsite emission measurements, entire life cycle stages (construction, infrastructure, etc.), and resource flow (net energy and material use) will provide a more precise environmental assessment. Furthermore, the technologies were assessed in stand-alone mode. The integration of two or more technologies might be able to maximise their benefits while complementing weaknesses. Also, value recovery from digestate and ash is essential to economic and environmental feasibility. Therefore, future research should investigate scenarios combining energy recovery technologies, including a holistic value chain and cost-benefit analysis. Energy scarcity and waste management are prominent challenges in Nigeria, yet energy recovery technologies are uncommon, given the abundance of potential. Therefore, there is a need to ascertain the willingness and awareness of operators and regulatory agencies in municipalities. Combining sludge with other forms of organic waste from municipal or agricultural sources in centralised facilities could be promising. Sludge treatment line optimisation, specifically energy-efficient sludge drying systems, can be explored, including sun drying and heat recovery systems.

The result of this study has several implications for the locality. HEP and AD options are viable from the perspective of energy generation and environmental impacts. The absence of these energy recovery technologies in Nigeria could be linked to high capital investment and a lack of technical know-how and expertise. However, HEP technology is not entirely new since it contributes significantly to the national electricity mix. Therefore, municipal governments, ministries of environment, water resources, and power should embark on pilot projects. Likewise, research institutions should be adequately empowered through fiscal allocation for such projects. Policies and regulatory frameworks that encourage energy recovery from waste should also be enacted with incentives such as government subsidies, tax rebates, and carbon credits. Such regulations will attract investments, especially from the public sector. Another option is the expansion of current policies, such as the Renewable Energy Master Plan and the National Environmental Sanitation Policy, which promote the adoption of these technologies and enhance energy access. In the long run, access to clean water and sanitation, increased access to clean and affordable energy, and responsible production and consumption are attainable with respect to the SDGs.

7.4 Conclusion

The energy recovery potential, economic feasibility, and environmental impacts of HEP, AD, and INC from a WWTP have been investigated. The HEP, INC, and AD technologies assessed in this study had electricity recovery potential of 30,889.56-147,451.11, 19,910.10-95,040.76, and 6,584.97-31,433.33 kWh/year, respectively.

The HEP had the best electricity generation potential and was primarily influenced by higher efficiency, capacity factor, and readily available flow. The energy generation potential of the technologies was directly proportional to the amount of diesel displaced in addition to related costs and emissions. Moreover, energy generation potential increases by more than 79% if the plant operates at full capacity.

HEP operations generally had insignificant environmental impacts, while AD performed better than INC. The INC technology contributed the most to climate change with a GWP of 9,168.27–43,764.67 kg CO_2 eq./yr. AD had a GWP of 4,858.7–23,195.3 kg CO_2 eq./yr, while HEP operations generally had insignificant environmental impacts compared to AD and INC. CO_2 emissions starred GWP values in INC, while CH_4 leakages governed the values in AD. AD contributed less to the potential ozone creation than INC. The POCP values for AD and INC were 3.62-17.3 and 1944.49-9282.03 kg NMOVC eq./yr, respectively. In terms of Acidification potential, AD was preferred. The values were 1.84-8.79 and 1406.94-6716.02 mol H+ eq./yr for AD and INC, respectively. Emissions of CO_2 and CH_4 were primary contributors to climate change, while NO_x accounted for 65-99% of POCP, AP, and PM. At the same time, CH_4 and NMVOC influenced FE and HTC.

AD outperforms other technologies in most economic indicators. AD was more feasible than HEP and INC, with the best values for LCC, IRR, LCOE, ACS, and PBP. It has a lower initial investment and a shorter payback. It favours investors interested in higher returns within the short term. HEP was also very competitive with the highest NPV; however, high costs make it suitable for projects with long-term perspectives. The INC appeared to be the least attractive based on the economic indicators. Moreover, the performance of the technologies is affected by fluctuations in plant capacity factor, electricity generation efficiency, capital and O&M cost, electricity tariff, and discount rate.

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8. Discussion

8.1 Overview of LCA studies of water and wastewater treatment technologies in Africa

Most reviewed studies were concentrated in South Africa and Egypt, with limited publication from other countries. Given the size of its GDP, population and water sector, the absence of studies from Nigeria was noteworthy. These studies mainly focused on the operation of treatment technologies and revealed the prevalence of urban wastewater encompassing rain runoff, sewerage, and industrial effluents. The activated sludge process was the dominant wastewater treatment method, followed by varied sludge management techniques, notably land application.

The quantitative analysis demonstrated how the water source, geographical location, and life cycle stage were critical drivers of variation in the energy use intensity at treatment facilities. The energy use intensity was directly proportional to the GWP. The software model, water source, life cycle stage, and publication year principally influenced the GWP. Electricity generation from fossil fuels was the main contributor to adverse environmental impacts. The key environmental categories assessed were climate change (including GWP) and ecotoxicity. The influence of energy source and usage intensity on the overall performance of WWTPs was emphasised.

A comparison with developed and other developing countries shows disparities. Adherence to standards is essential for sustainability evaluations, but limited studies in Africa were a concern. It highlights the need for technological advancements in Africa's water sector. Other challenges included limited data availability and expanding data storage and acquisition. The reliance on fossil fuels for electricity contributes to adverse impacts, emphasising the importance of transitioning to renewable energy sources. Addressing these problems requires a multi-pronged approach, including encouraging comparative assessments and technology transfer across nations to narrow the gap between Africa and developed regions. However, the lack of stakeholder consideration in this analysis might hinder capturing real-world insights, while the limited studies selected might affect applicability. Further research is needed to enhance LCA methodologies, specifically regional emission and characterisation factor models. A robust data infrastructure is crucial for harnessing the sustainable potential of water purification in Africa and beyond. Encouraging collaboration among stakeholders in LCA studies and integrating life cycle thinking into engineering designs are essential for holistic solutions. Implementing such solutions demonstrates an organisation's eco-responsibility and commitment to footprint reduction. Regulators should set standards and incentives for eco-friendly solutions.

8.2 Potential Environmental Pollution from WWTPs in Nigeria

The WWTP demonstrates robust COD, BOD, and TSS removal exceeding 90%, attributed to advanced biological and sedimentation techniques. However, the variability in pollutant TE, especially for NO_3-N, FCC, and BOD, underscores challenges in meeting standards consistently, warranting further investigation into influencing factors. Compliance relies on precise monitoring and treatment parameter adjustments. However, nutrient and organic matter emissions underline potential pollution sources for receiving waterbodies. In rivers and lakes, pollutants in effluent harm water quality and aquatic life, while nutrients cause eutrophication, resulting in habitat degradation, species displacement, biodiversity losses, and ecosystem imbalance. Also, the sludge generated at the WWTPs is primarily accumulated onsite while small amounts are used as soil fertilisers after onsite drying. There is a potential deposition of heavy metals and micropollutants in sludge and effluent during agricultural land application, leading to ecotoxicity.

Biological activities of the activated sludge process drive the emissions of GHGs at the WWTP. Biological wastewater treatment accounted for while methane constituted over 80 and 68% of total emissions, respectively. Electricity consumption was the main driver of offsite emissions, while carbon dioxide was the most significant offsite emission, primarily linked to electricity. The estimated energy consumption of the WWTP was 0.54 kWh/m^3, equivalent to 10,192.15 kWh/d. The anoxic mixers (3,610 kWh/d), oxidation blowers (3,040 kWh/d), and UV lamps (2,090 kWh/d) were the highest electricity consumers and emitted 968.71, 815.76, and 560.83 kg CO_2-eq./d of GHG, respectively. Hence, the aeration basin was the principal contributor to overall GHG emissions since most biological processes occur here, and electricity is consumed by aerators and mixers that enhance the process. The effluent discharge and use of chemicals in sludge treatment were also a source of GHG emissions. Volatilisation of contaminants from effluent may contribute to air pollution, especially for volatile organic compounds and gases. Therefore, mitigation measures towards emissions from the aeration basin are crucial for achieving carbon neutrality at WWTPs.

Overall, the study emphasises that addressing issues highlighted by yearly variations requires a targeted approach, emphasising the need for a comprehensive operational strategy that considers seasonal influences and potential challenges in maintaining treatment performance. Additionally, deploying IoT technology in innovative and intelligent management systems for possible remote control and optimised operation of aeration, pumping, and dosing units increases energy efficiency, further diminishing GHG emissions.

8.3 Opportunities for energy recovery from wastewater and sludge

The energy recovery landscape within the wastewater value chain was demonstrated. The volume of wastewater generation and centralised collection was estimated to determine sludge production potential. The estimated wastewater generation in Nigeria was about 1,047,970,749.67 m^3/year, while 55,130,851.19 m^3/year was collected, resulting in a sludge generation of approximately 677,808.52 tonnes/year (wet-basis). The resulting average electrical energy potential is 24.26 and 0.73 GWh/year for AD and INC technologies, respectively. AD is the most technically feasible alternative across zones for electricity generation but is highest in NC, SS, and SE, with a potential of 6.8, 6.3, and 4.1 GWh/yr, respectively. The study focused on only sewer collection, which implies higher energy potential if all collection types were included. Water access, population growth, and sewer connection rates affected energy potential.

At the WWTP, 27,496-131,250 m^3/d is treated annually, potentially generating 760,508.141-3,630,280.989 kg (30% dry solids) dewatered sludge. These resources afford energy recovery by INC of sludge, biogas from AD of sludge, or integrated HEP at inflow or outflow point. The HEP demonstrated the highest potential, followed by INC and AD. The annual electricity recovery potential for HEP, INC and AD was 30,889.56-147,451.11, 19,892.86-94,958.47, and 6,584.97-31,433.33 kWh, respectively. With a potential displacement of 947, 918, and 895 thousand litres of diesel per year, respectively. Compared with an annual electricity demand of 3,720,134.75 kWh, the energy potential of HEP, INC, and AD could cover 0.83-3.96%, 0.53-2.55%, and 0.18-0.84%, respectively.

The technical peculiarities in selecting centralised and decentralised energy recovery technologies are evident. INC is more suitable for centralised systems and is often preferred due to minor space/land area requirements than AD. INC also has a higher sludge volume reduction efficiency. HEP is superior due to its higher electricity generation efficiency and capacity factor than AD and INC. The potential of HEP depends on the available head, flow rate, hydraulic losses, and turbine efficiency. At the same time, AD and INC are generally affected by sludge characteristics, operational temperature, and contact time. Sludge drying is another major factor which affects the net energy balance of AD and INC.

Therefore, knowledge of wastewater generation and collection patterns would inform policymakers on allocating public utilities and infrastructure properly. Unfortunately, investing in these renewable energy technologies seems untenable. However, it is necessary to investigate further an integrated system that may include one or more HEP, INC, and AD, possibly diesel generators and grid electricity.

8.4 Assessment of the economic feasibility of scenarios for energy recovery

The economic dynamics in selecting centralised and decentralised energy recovery technologies were realised. The AD had a competitively higher NPV and shorter PBP at the regional level. However, INC technology appeared more viable than AD. INC had lower LCC, LCOE, and ACS values and a higher IRR. The total cost of the AD project, including capital costs and O&M costs, was higher. On the other hand, at the WWTP level, AD was the most preferred, while INC was the least preferred economically. The LCC, IRR, LCOE, ACS, and breakeven time values of AD were better than those of HEP and INC. The competitive NPV of HEP was diminished by its high-cost components.

However, the model for estimating cost may depend highly on the capacity of the system. Moreover, other economic metrics rely on the cost; thus, there seems to be a linear snowballing effect where the higher potential gives more preferred economic feasibility. In future, incorporating more site-specific parameters (data) into the model might provide a more accurate representation of energy potential and economic viability. Nonetheless, the economic outlook depends on sludge generation rate, sludge characteristics, calorific value (sludge and methane), wastewater flow rate, electricity generation efficiency, electricity tariff, plant capacity factor, discount rate, capital and O&M cost, and population growth rate.

Additionally, it follows that the complexity and sophistication of a technology also impact its initial investment. Economic metrics analysed in this study were influenced by changes in plant capacity factor, electricity generation efficiency, capital and O&M cost, electricity tariff, and discount rate, which affected the performance. It also reemphasises the sensitivity analysis results, which showed that increased sludge generation and electricity tariffs raise the economic viability of WtE systems. Profitability varied with technology type and depended on cost, discount rate, and electricity tariff. Therefore, the selection between technologies ought to reflect the fiscal goal and priorities of the project. For instance, projects focusing on quick investment recovery might prefer technologies with shorter payback periods, while those with long-term views may be attracted to lower initial costs.

8.5 Evaluation of the environmental impact of energy recovery scenarios

The environmental impacts of HEP, AD, and HEP concerning air emissions were characterised. Emissions to air due to HEP operations were adjudged negligible and hence ignored. The critical emissions to air considered were CH_4, NMVOC, CO_2, N_2O, CO, NO_x, and SO_2. The annual generation of these gases by INC was 21.5-102.6, 43-205.3, 7,167.6-34,214.7, 0.29-1.4, 11,787.9-56,269.4, 1,901.3-9,075.7, and 7.58E-04 – 3.6E-03 kg, respectively. The values for AD were 111.9-534.3, 0.11-0.57, 1,518.7-725, 0.0024-0.0113, 1.2-5.7, 2.4-11.3, and 0.07-0.3 kg per year, respectively. The most generated emissions were CO, CO_2, and NO_x for INC, and AD emitted more CO_2, CH_4, and NO_x.

The equivalent annual impacts on climate change expressed in terms of GWP by INC was 9,168.27-43,764.67 kg CO2 eq. In comparison, AD had 4,858.7-23,195.3 kg CO_2 eq. The POCP values for AD and INC were 3.62-17.3 and 1,944.49-9,282.03 kg NMOVC eq./yr, respectively. In terms of Acidification potential, AD was preferred. The values were 1.84-8.79 and 1,406.94-6,716.02 mol H+ eq./yr for AD and INC, respectively. INC also had higher impacts on Aquatic Ecotoxicity, Non-Cancer Human Health Effects, and Respiratory Inorganics. Although NO_x was not the most emitted, it demonstrated the most adverse environmental effects. Emissions of CO_2 and CH_4 were central to climate change impact, while NO_x accounted for 65-99% of acidification, Respiratory Inorganics, and Photochemical Ozone Creation. Non-Cancer Human Health Effects and Aquatic Ecotoxicity were affected by the emission of CH_4 and NMVOC. Emissions of NO_x and SO_2 are linked to the Nitrogen and Sulphur content of the sludge. Exhaust emissions from combustion significantly cause adverse environmental impacts. They can be contained by implementing advanced combustion technologies and air pollution control systems such as catalytic reduction and gas desulphurisation.

Ultimately, investment in the assessed technologies seems untenable based on their capacities. However, these technologies can be integrated into the WWTP, adversely affecting its performance. Also, INC and AD may have impacts, but they are lower than diesel and fossil fuel. Moreover, these technologies treat organic waste; thus, the energy recovered offsets the potential environmental impacts. Additionally, in the disposal of sludge, these technologies reduce transportation costs and the volume of sludge to be managed while lessening the pressure on and emissions from landfills. Furthermore, it is necessary to investigate an integrated system that meets the energy demand, is cost-effective, and is environmentally friendly. This system may include one or more HEP, INC, and AD, possibly diesel generators and grid electricity.

9. Conclusion

The implementation of LCA has generally evolved in Africa. Most researchers are interested in understanding several treatment technologies and enhancing the performance of existing systems. The GWP, an indication of climate change, was the most assessed impact category, while electricity from fossil fuels was the main contributor to adverse impacts. Hence, this thesis points out the need for increased renewable energy use, resource recovery, data acquisition and storage to compensate for environmental and economic costs in the water sector. Additionally, more is desired, particularly in Nigeria, where reports on the LCA of water and wastewater treatment were absent from the literature. Integrating LCA into local environmental standards, engineering designs, and academic curricula in relevant programmes at higher institutions is recommended.

The assessment of plant efficiency showed a high removal efficiency for organic matter and coliforms influenced mainly by enhanced oxygenation in the aeration basin. However, nitrates, coliforms, and organic matter removal were inconsistent with standards and present potential pollution to receiving waterbodies. Nutrient enrichment leads to eutrophication, detrimental to aquatic life and ecosystems. Additionally, GHG emissions from WWTPs are possible sources of GWP. The methane emissions from biological activities of the activated sludge process contribute significantly. Generally, the aeration basin was a significant contributor to GHG emissions.

The data gap relating to wastewater generation and distribution in Nigeria was filled. The energy potential within this value chain and the expected economic implications were presented. Access to water, population growth rates, and sewer connections affected energy potential across the country. The volatile solids in sludge and the kinetic energy of wastewater flow have presented potential sources of energy recovery in the water industry. The southern region of Nigeria had the highest potential for energy generation, primarily by the installation of biogas plants. Hydroelectric power generation was more beneficial for treatment plants.

AD was profitable both at regional and facility levels. However, its capacity at the treatment plant was poor. AD demonstrated competitive NPV and the shortest payback period at all levels. HEP had desirable LCOE and NPV; however, most cost elements were unattractive. INC was more economical at a centralised level and had less space requirements. Comparative analyses showed that the technology with higher capacity translates to higher viability, which may not be the case in real-world applications. Due to several factors affecting profitability, the policy and priorities of a project would affect the choice of technology. Long-term perspectives favour HEP and INC, while short-term investments align with AD.

The operation of HEP has insignificant emissions. The annual emissions from INC were higher than those from AD. The yearly environmental impacts of AD were superior to INC across all categories considered. However, based on impacts per kWh, INC outperformed AD in climate change and non-cancer human health effects categories. The highest emissions from INC were CO, CO_2, and NO_x, while AD released more CO_2, CH_4, and NO_x gases. Emissions of NO_x had the most significant environmental impact, responsible for a substantial portion of acidification, Respiratory Inorganics, and Photochemical Ozone Creation in AD and INC. Mitigation measures against exhaust emissions will considerably reduce emissions. The energy recovered from AD and INC could be considered offset for their environmental impacts.

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Appendices

Appendix A

S1. Search Keywords & Data Analysis

Thoroughly fashioned strings of keywords were used to search for papers available up to December 2021 linked to the theme of this review. Keywords such as "water"; "wastewater"; "wastewater"; “sludge”; “treatment”; “life cycle”; “lifecycle”; “environmental”; “assessment”; “analysis”; “LCA”; “greenhouse gases”; GHG”; “carbon dioxide”; “CO_2” were used. The outcomes were supplemented by location (Africa) and the most populous African countries as "Africa"; "South Africa"; "Egypt"; "Ghana"; "Kenya"; "Mali"; "Morocco"; "Uganda"; "Ethiopia"; "Congo"; "Algeria"; "Nigeria"; "Mozambique"; "Cameroon"; "Niger"; "Tanzania"; "Sudan"; "Angola"; "Madagascar"; "Ivory Coast"; "Burkina Faso".

For a valid statistical analysis, the data samples were grouped based on energy use and EIs and further grouped by study location, publication year, water source, software used, LCA stage, and impact assessment method. These groups were meta-analyzed. Heterogeneity was tested using the Q statistic. When p-value > 0.1 and $I^2 \leq 40\%$, the heterogeneity between the studies was insignificant, indicating that a fixed-effect model, else a random effect model, was chosen [6]. The factors affecting the outcome of LCA studies have been categorized into technical data, methodological choices, and study typology [13]. Tab. 1 shows a summary of groups and subgroups of variables that affect the results of LCA studies adapted from [13]. These variables can also be generally classified as independent variables, while energy use, GWP, and EP are the dependent variables. The study by Li et al. [6] assessed only the effects of technical factors on the environmental performance of WWTPs. Thus, this study selects variables across the three categories with a substantial influence on outcomes as a hint in the mentioned studies: water source, study location, life cycle stage, life cycle impact assessment (LCIA) methodology, software, and year of publication. For the present study, the year of publication is also described as the year of study. Furthermore, all statistical analyses were completed using the meta [19] or metaphor [20] packages in R software [21].

It should also be noted that, unlike conventional studies, LCA studies do not report variances for each observation. On the study level, the standard deviation was calculated based on all observations for a source of water (raw or wastewater (WW)). For each variable (energy and EIs), two different means are estimated: (i) the weighted or pooled mean calculated by using the inverse variance pooling method (using *metamean* function in R). The *metamean* function estimates the overall mean from single means reported in selected studies using the inverse variance pooling method. The overall mean is estimated using the inverse variance method, the restricted maximum-likelihood estimator for tau^2, the Q-profile method for the confidence interval of tau^2 and tau, and the Hartung-Knapp adjustment for random effects models. (ii) the arithmetic mean. Though both estimates are presented for comparison's sake and appraisal since the outcomes were occasionally similar, only the arithmetic mean is discussed throughout this paper. A possible reason for the disparity between the results of the two methods is that the pooling method assigns no weight to observations with no variance.

Additionally, a meta-regression analysis was performed to further clarify to what extent the factors influenced energy use and EIs. Since various databases and modelling approaches were used in the primary studies being considered, it is assumed that heteroskedasticity exists. White's Heteroskedastic Consistent Covariance Matrix (HCCM) was used for correction. Given that variances per observation are absent in LCA studies, the ordinary least square (OLS) was used to fit the meta-regression model. The HCCM and OLS were achieved with the *lmtest* package in R. The results of this analysis were used to estimate the importance of factors on the outcome of water treatment-related LCA studies.

Table 1. A selection of variables considered in LCA studies of water treatment.

Variables Family	Description of variables	Variables
TECHNICAL DATA		
Source of water		
	Wastewater	WW
	Domestic wastewater	domestic WW
	Urban wastewater	urban WW
	Industrial wastewater	industrial WW
	Raw water/sources, e.g., rivers, dams, sea	raw water (RW)
Geographical location	Country of case study	location South Africa, Egypt, Cameroon, Morocco
METHODOLOGICAL CHOICES		
Life cycle stages		LC stage
	Construction, Operation, Demolition	C/O/D
	Construction, Operation	C/O
	Operation	O
LCIA methodologies		
	CML	CML
	ReCiPe	ReCiPe
	Eco-indicator	
	others besides CML, ReCipe, Eco-indicator	Others
Software		
	SimaPro	SimaPro
	GaBi	GaBi
	ACV4E	ACV4E
	Unspecified	n.a.
STUDY TYPOLOGY		
Year of publication		year

S2. Statistical Summary

Table S1. Statistical description of energy use and EIs for water & wastewater treatment (n= number of observations).

	Energy Use (KWh/m^3)						**Global warming potential** (kg CO_2-eq/m^3)						**Eutrophication potential** (kg PO_4^{3-}-eq/m^3)					
Locations	n	Min.	Max.	Median	Mean	stdDev	n	Min.	Max.	Median	Mean	stdDev	n	Min.	Max.	Median	Mean	stdDev
All	32	0.001	77.87	0.4028	8.184	16.993	20	1.69E-14	15.87245	0.3275	2.171609	4.081342	20	1.3E-15	0.27227	0.0003	0.0383	0.081344
South Africa	12	0.001	46.538	3.1595	11.422	15.808	9	0.094	4.4	0.481	1.040667	1.478629	9	0.000033	0.00442	0.000	0.0009	0.001578
Egypt	13	0.011	0.4028	0.0109	0.087	0.142	7	1.69E-14	0.346	2.17E-14	0.108571	0.154762	7	1.3E-15	0.01637	1E-14	0.0040	0.006115
others	7	0.0028	77.87	8.142	17.671	27.672	4	1.607909	15.87245	7.912909	8.326545	5.944693	4	0.070545	0.27227	0.194	0.1828	0.083777
Source	n	Min.	Max.	Median	Mean	stdDev	n	Min.	Max.	Median	Mean	stdDev	n	Min.	Max.	Median	Mean	stdDev
industrial WW	7	0.319	34.052	5.851	12.215	13.476	2	0.094	2.6	1.347	1.347	1.7720096	2	0.000033	0.0027	0.001	0.00139	0.001931
municipal WW	19	0.003	23.403	0.057	2.471	5.778	12	1.69E-14	15.872455	0.207	2.8472652	5.1016659	12	1.3E-15	0.2723	0.006	0.06331	0.098662
raw water	6	0.001	77.87	2.213	21.572	33.021	6	0.185	4.4	0.5075	1.0951667	1.6286352	6	0.000056	0.0044	0.000	0.00089	0.001729
Stage	n	Min.	Max.	Median	Mean	stdDev	n	Min.	Max.	Median	Mean	stdDev	n	Min.	Max.	Median	Mean	stdDev
C/O/D	10	0.003	23.403	0.667	4.796	7.362	9	0.105	15.87245	0.346	3.837909	5.602702	9	0.0000569	0.27227	0.016	0.08443	0.106667
C/O	8	0.057	12.875	0.195	2.411	4.434	9	1.69E-14	4.4	0.094	0.852888	1.574151	9	1.3E-15	0.00442	0.000	0.00082	0.001621
O	14	0.001	77.87	0.011	13.903	23.999	2	0.534	0.681	0.6075	0.6075	0.103944	2	0.0003	0.00033	0.000	0.00031	2.121E-05

Table S1. Statistical description of energy use and EIs for water & wastewater treatment (n= number of observations) continued.

	Energy Use (KWh/m^3)						**Global warming potential** (kg CO_2-eq/m^3)						**Eutrophication potential** (kg PO_4^{3-}-eq/m^3)					
LCIA Method	n	Min.	Max.	Median	Mean	stdDev	n	Min.	Max.	Median	Mean	stdDev	n	Min.	Max.	Median	Mean	stdDev
CML	9	0.001	46.538	0.072	5.382	15.436	11	1.69E-14	0.681	0.101	0.2151	0.2467	11	1.3E-15	0.00033	0.0000351	9.403E-05	0.0001244
ReCiPe	6	0.003	3.690	0.403	1.131	1.480	5	0.105	4.4	0.346	1.552	1.8909	5	0.0027	0.01637	0.005924	0.0070808	0.0053542
Unspecified	4	5.966	23.403	8.163	11.424	8.053	4	1.60790	15.872	7.9129	8.3265	5.945	4	0.0705	0.2722	0.1943636	0.1828864	0.0837777
Eco-Indicator 99	8	0.011	77.870	0.011	9.743	27.527												
impact 2002+	4	2.629	34.052	16.736	17.538	15.634												
IPCC	1	12.876	12.875	12.875	12.875	0.000												
Software	n	Min.	Max.	Median	Mean	stdDev	n	Min.	Max.	Median	Mean	stdDev	n	Min.	Max.	Median	Mean	stdDev
GaBi	5	0.319	0.736	0.403	0.492	0.171	5	0.094	0.481	0.185	0.2302	0.1610	5	0.000033	0.0002	0.00005	8.086E-05	7.139E-05
SimaPro	17	0.001	77.870	2.160	12.551	21.937	7	0.105	4.4	0.534	1.2821	1.6118	7	0.0003	0.01637	0.00442	0.00514	0.00547
n.a.	8	0.057	23.403	3.019	5.742	8.043	8	1.69E-14	15.872	0.8039	4.1632	5.9122	8	1.3E-15	0.2722	0.03527	0.0914	0.11209
ACV4E	2	0.003	0.127	0.065	0.065	0.088												
Year	n	Min.	Max.	Median	Mean	stdDev	n	Min.	Max.	Median	Mean	stdDev	n	Min.	Max.	Median	Mean	stdDev
2002	3	0.319	0.736	0.599	0.551	0.212	3	0.094	0.29	0.185	0.1896	0.0980	3	0.00003	0.00007	0.00006	5.473E-05	2.044E-05
2009	-	-	-	-	-	-	2	0.101	0.481	0.291	0.291	0.2687	2	0.00004	0.0002	0.0001	0.0001	0.0001
2010	4	0.011	0.011	0.011	0.011	0.000	-	-	-	-	-	-	-	-	-	-	-	-
2012	9	0.002	46.538	2.629	12.969	18.082	2	0.534	0.681	0.6075	0.6075	0.1039	2	0.0003	0.0003	0.000315	0.000315	2.121E-05
2014	-	-	-	-	-	-	3	0.105	0.346	0.309	0.2533	0.1297	3	0.0059	0.016	0.005925	0.0094	0.0060
2016	5	5.966	77.870	8.183	24.713	30.523	4	1.6079	15.872	7.9129	8.3265	5.9446	4	0.0705	0.2722	0.1943	0.1828	0.0837
2018	1	12.875	12.875	12.875	12.875	0.000	-	-	-	-	-	-						
2019	6	0.057	3.690	0.064	1.016	1.556	6	1.69E-14	4.4	2.165E-14	1.1666	1.8949	6	1.3E-15	0.004	1E-14	0.001	0.0019
2020	4	0.003	0.403	0.265	0.234	0.202												

S3. Results of the pooled mean (metamean)

```
> summary(energy.mean21)
Review:     Energy Use (kWh/m^3)

                              mean             95%-CI %W(random)
Aime et al 2016            11.4235 [  3.5315;  19.3155]        5.4
Awad et al 2019             0.0608 [  0.0538;   0.0678]       10.2
Bahi et al 2020             0.0651 [ -0.0569;   0.1870]       10.2
Fernandez-Torres et al 2012 17.5383 [  2.2174;  32.8591]        2.4
Friedrich 2002              0.6674 [  0.5330;   0.8017]       10.2
Goga et al 2019a            3.6900 [-11.9842;  19.3642]        2.3
Goga et al 2019b            2.1600 [  1.0097;   3.3103]       10.0
Mahgoub et al 2010          0.0109 [ -0.9855;   1.0073]       10.0
Masindi et al 2018         12.8750 [  9.8251;  15.9249]        9.0
Morsy et al 2020            0.4028 [ -0.8976;   1.7032]        9.9
Pillay et al 2002           0.3194 [ -1.5524;   2.1912]        9.7
Ras and von Blottnitz 2012 23.2695 [-22.3366;  68.8756]        0.3
Roushdi et al 2012          0.0109 [ -1.1396;   1.1614]       10.0
Zhang & Prouty 2016        77.8700 [ 28.5238; 127.2162]        0.3

Number of studies combined: k = 14
Number of observations: o = 32

                       mean            95%-CI
Random effects model 2.9610 [-0.8736; 6.7957]

Quantifying heterogeneity:
 tau^2 = 18.6662 [13.4481; >186.6624]; tau = 4.3204 [3.6672; >13.6624]
 I^2 = 92.9% [89.7%; 95.1%]; H = 3.75 [3.12; 4.50]

Test of heterogeneity:
      Q d.f.  p-value
 182.70   13 < 0.0001

Details on meta-analytical method:
- Inverse variance method
- Restricted maximum-likelihood estimator for tau^2
- Q-profile method for confidence interval of tau^2 and tau
- Hartung-Knapp adjustment for random effects model
- Untransformed (raw) means
> 
```

Figure S1. Result of the pooled mean of energy use.

```
> summary(energy.mean.loc21)
Review:     Energy Use (kWh/m^3)

                               mean              95%-CI %W(random)  sublocation
Aime et al 2016             11.4235 [  3.5315;  19.3155]       5.4       others
Awad et al 2019              0.0608 [  0.0538;   0.0678]      10.2        Egypt
Bahi et al 2020              0.0651 [ -0.0569;   0.1870]      10.2       others
Fernandez-Torres et al 2012 17.5383 [  2.2174;  32.8591]       2.4 South Africa
Friedrich 2002               0.6674 [  0.5330;   0.8017]      10.2 South Africa
Goga et al 2019a             3.6900 [-11.9842;  19.3642]       2.3 South Africa
Goga et al 2019b             2.1600 [  1.0097;   3.3103]      10.0 South Africa
Mahgoub et al 2010           0.0109 [ -0.9855;   1.0073]      10.0        Egypt
Masindi et al 2018          12.8750 [  9.8251;  15.9249]       9.0 South Africa
Morsy et al 2020             0.4028 [ -0.8976;   1.7032]       9.9        Egypt
Pillay et al 2002            0.3194 [ -1.5524;   2.1912]       9.7 South Africa
Ras and von Blottnitz 2012  23.2695 [-22.3366;  68.8756]       0.3 South Africa
Roushdi et al 2012           0.0109 [ -1.1396;   1.1614]      10.0        Egypt
Zhang & Prouty 2016         77.8700 [ 28.5238; 127.2162]       0.3       others

Number of studies combined: k = 14
Number of observations: o = 32

                       mean            95%-CI
Random effects model 2.9610 [-0.8736; 6.7957]

Quantifying heterogeneity:
 tau^2 = 18.6662 [13.4481; >186.6624]; tau = 4.3204 [3.6672; >13.6624]
 I^2 = 92.9% [89.7%; 95.1%]; H = 3.75 [3.12; 4.50]

Test of heterogeneity:
      Q d.f.  p-value
 182.70   13 < 0.0001

Results for subgroups (random effects model):
                            k    mean               95%-CI     tau^2     tau     Q   I^2
sublocation = others        3 23.1216 [-72.0317; 118.2749] 1087.0682 32.9707 17.50 88.6%
sublocation = Egypt         4  0.0608 [  0.0573;   0.0643]         0       0  0.28  0.0%
sublocation = South Africa  7  5.1243 [ -1.0972;  11.3457]   32.4609  5.6974 73.49 91.8%

Test for subgroup differences (random effects model):
                    Q d.f. p-value
Between groups   5.05    2  0.0799

Details on meta-analytical method:
- Inverse variance method
- Restricted maximum-likelihood estimator for tau^2
- Q-profile method for confidence interval of tau^2 and tau
- Hartung-Knapp adjustment for random effects model
- Untransformed (raw) means
> 
```

Figure S2. Subgroup analysis result for energy use by location.

```
Review:     Energy Use (kWh/m^3)

                             mean                95%-CI %W(random)     subsource
Aime et al 2016           11.4235 [  3.5315;  19.3155]        5.4  Municipal WW
Awad et al 2019            0.0608 [  0.0538;   0.0678]       10.2  Municipal WW
Bahi et al 2020            0.0651 [ -0.0569;   0.1870]       10.2  Municipal WW
Fernandez-Torres et al 2012 17.5383 [  2.2174;  32.8591]        2.4 industrial WW
Friedrich 2002             0.6674 [  0.5330;   0.8017]       10.2     raw water
Goga et al 2019a           3.6900 [-11.9842;  19.3642]        2.3     raw water
Goga et al 2019b           2.1600 [  1.0097;   3.3103]       10.0 industrial WW
Mahgoub et al 2010         0.0109 [ -0.9855;   1.0073]       10.0  Municipal WW
Masindi et al 2018        12.8750 [  9.8251;  15.9249]        9.0 industrial WW
Morsy et al 2020           0.4028 [ -0.8976;   1.7032]        9.9  Municipal WW
Pillay et al 2002          0.3194 [ -1.5524;   2.1912]        9.7 industrial WW
Ras and von Blottnitz 2012  23.2695 [-22.3366;  68.8756]        0.3     raw water
Roushdi et al 2012         0.0109 [ -1.1396;   1.1614]       10.0  Municipal WW
Zhang & Prouty 2016       77.8700 [ 28.5238; 127.2162]        0.3     raw water

Number of studies combined: k = 14
Number of observations: o = 32

                       mean            95%-CI
Random effects model 2.9610 [-0.8736; 6.7957]

Quantifying heterogeneity:
 tau^2 = 18.6662 [13.4481; >186.6624]; tau = 4.3204 [3.6672; >13.6624]
 I^2 = 92.9% [89.7%; 95.1%]; H = 3.75 [3.12; 4.50]

Test of heterogeneity:
      Q d.f.  p-value
 182.70   13 < 0.0001

Results for subgroups (random effects model):
                            k    mean              95%-CI    tau^2     tau     Q   I^2
subsource = Municipal WW    6  0.0609 [  0.0483;  0.0734]  <0.0001  0.0013  8.25 39.4%
subsource = industrial WW   4  6.6506 [ -5.5374; 18.8386]  47.2590  6.8745 53.40 94.4%
subsource = raw water       4 19.0944 [-32.3981; 70.5869] 668.9914 25.8649 10.49 71.4%

Test for subgroup differences (random effects model):
                    Q d.f. p-value
Between groups   4.34    2  0.1139

Details on meta-analytical method:
- Inverse variance method
- Restricted maximum-likelihood estimator for tau^2
- Q-profile method for confidence interval of tau^2 and tau
- Hartung-Knapp adjustment for random effects model
- Untransformed (raw) means
> 
```

Figure S3. Subgroup analysis result for energy use by water source.

```
Review:     Energy Use (kWh/m^3)

                              mean               95%-CI %W(random) water
Aime et al 2016            11.4235 [  3.5315;  19.3155]        5.4    WW
Awad et al 2019             0.0608 [  0.0538;   0.0678]       10.2    WW
Bahi et al 2020             0.0651 [ -0.0569;   0.1870]       10.2    WW
Fernandez-Torres et al 2012 17.5383 [  2.2174;  32.8591]        2.4    WW
Friedrich 2002              0.6674 [  0.5330;   0.8017]       10.2    RW
Goga et al 2019a            3.6900 [-11.9842;  19.3642]        2.3    RW
Goga et al 2019b            2.1600 [  1.0097;   3.3103]       10.0    WW
Mahgoub et al 2010          0.0109 [ -0.9855;   1.0073]       10.0    WW
Masindi et al 2018         12.8750 [  9.8251;  15.9249]        9.0    WW
Morsy et al 2020            0.4028 [ -0.8976;   1.7032]        9.9    WW
Pillay et al 2002           0.3194 [ -1.5524;   2.1912]        9.7    WW
Ras and von Blottnitz 2012  23.2695 [-22.3366;  68.8756]        0.3    RW
Roushdi et al 2012          0.0109 [ -1.1396;   1.1614]       10.0    WW
Zhang & Prouty 2016        77.8700 [ 28.5238; 127.2162]        0.3    RW

Number of studies combined: k = 14
Number of observations: o = 32

                      mean           95%-CI
Random effects model 2.9610 [-0.8736; 6.7957]

Quantifying heterogeneity:
 tau^2 = 18.6662 [13.4481; >186.6624]; tau = 4.3204 [3.6672; >13.6624]
 I^2 = 92.9% [89.7%; 95.1%]; H = 3.75 [3.12; 4.50]

Test of heterogeneity:
      Q d.f.  p-value
 182.70   13 < 0.0001

Results for subgroups (random effects model):
             k    mean              95%-CI    tau^2     tau     Q   I^2
water = WW  10  2.9636 [ -0.9438;  6.8710]  21.2560  4.6104 93.92 90.4%
water = RW   4 19.0944 [-32.3981; 70.5869] 668.9914 25.8649 10.49 71.4%

Test for subgroup differences (random effects model):
                    Q d.f. p-value
Between groups   0.98    1  0.3215

Details on meta-analytical method:
- Inverse variance method
- Restricted maximum-likelihood estimator for tau^2
- Q-profile method for confidence interval of tau^2 and tau
- Hartung-Knapp adjustment for random effects model
- Untransformed (raw) means
```

Figure S4. Subgroup analysis result for energy use by water source.

```
Review:     GWP (kg CO2-eq/m^3)

                            mean             95%-CI %W(random)
Aime et al 2016           8.3300 [ 2.5089; 14.1511]        1.5
Awad et al 2019           0.0000 [ 0.0000;  0.0000]       12.8
Friedrich 2002            0.2380 [ 0.1350;  0.3410]       12.8
Friedrich et al 2009a     0.4810 [-0.0580;  1.0200]       12.0
Friedrich et al 2009b     0.1010 [-1.2749;  1.4769]        9.0
Goga et al 2019a          4.4000 [ 1.4993;  7.3007]        4.4
Goga et al 2019b          2.6000 [ 2.5821;  2.6179]       12.8
Pillay et al 2002         0.0940 [-1.2858;  1.4738]        9.0
Ras and von Blottnitz 2012 0.0003 [ 0.0003;  0.0003]       12.8
Risch et al. 2014         0.2530 [ 0.1059;  0.4001]       12.8

Number of studies combined: k = 10
Number of observations: o = 20

                      mean            95%-CI
Random effects model 0.7912 [-0.3220; 1.9043]

Quantifying heterogeneity:
 tau^2 = 1.1592 [0.6732; 19.8159]; tau = 1.0766 [0.8205; 4.4515]
 I^2 = 0.0% [0.0%; 62.4%]; H = 1.00 [1.00; 1.63]

Test of heterogeneity:
    Q d.f. p-value
 0.00    9  1.0000

Details on meta-analytical method:
- Inverse variance method
- Restricted maximum-likelihood estimator for tau^2
- Q-profile method for confidence interval of tau^2 and tau
- Hartung-Knapp adjustment for random effects model
- Untransformed (raw) means
>
```

Figure S5. Result of the pooled mean of global warming potential.

```
Review:     GWP (kg CO2-eq/m^3)

                             mean             95%-CI %W(random)  sublocation
Aime et al 2016            8.3300 [ 2.5089; 14.1511]        1.5       others
Awad et al 2019            0.0000 [ 0.0000;  0.0000]       12.8        Egypt
Friedrich 2002             0.2380 [ 0.1350;  0.3410]       12.8 South Africa
Friedrich et al 2009a      0.4810 [-0.0580;  1.0200]       12.0 South Africa
Friedrich et al 2009b      0.1010 [-1.2749;  1.4769]        9.0 South Africa
Goga et al 2019a           4.4000 [ 1.4993;  7.3007]        4.4 South Africa
Goga et al 2019b           2.6000 [ 2.5821;  2.6179]       12.8 South Africa
Pillay et al 2002          0.0940 [-1.2858;  1.4738]        9.0 South Africa
Ras and von Blottnitz 2012 0.0003 [ 0.0003;  0.0003]       12.8 South Africa
Risch et al. 2014          0.2530 [ 0.1059;  0.4001]       12.8        Egypt

Number of studies combined: k = 10
Number of observations: o = 20

                       mean            95%-CI
Random effects model 0.7912 [-0.3220; 1.9043]

Quantifying heterogeneity:
 tau^2 = 1.1592 [0.6732; 19.8159]; tau = 1.0766 [0.8205; 4.4515]
 I^2 = 0.0% [0.0%; 62.4%]; H = 1.00 [1.00; 1.63]

Test of heterogeneity:
    Q d.f. p-value
 0.00    9  1.0000

Results for subgroups (random effects model):
                             k   mean             95%-CI  tau^2    tau        Q    I^2
sublocation = others         1 8.3300 [ 2.5089; 14.1511]     --     --     0.00     --
sublocation = Egypt          2 0.1154 [-1.4857;  1.7165] 0.0292 0.1708     8.52  88.3%
sublocation = South Africa   7 0.8853 [-0.4252;  2.1958] 1.3838 1.1763 80932.28 100.0%

Test for subgroup differences (random effects model):
                    Q d.f. p-value
Between groups   9.52    2  0.0086

Details on meta-analytical method:
- Inverse variance method
- Restricted maximum-likelihood estimator for tau^2
- Q-profile method for confidence interval of tau^2 and tau
- Hartung-Knapp adjustment for random effects model
- Untransformed (raw) means
```

Figure S6. Subgroup analysis result for global warming potential by location.

```
Review:     GWP (kg CO2-eq/m^3)

                            mean             95%-CI %W(random)     subsource
Aime et al 2016           8.3300 [ 2.5089; 14.1511]        1.5  Municipal WW
Awad et al 2019           0.0000 [ 0.0000;  0.0000]       12.8  Municipal WW
Friedrich 2002            0.2380 [ 0.1350;  0.3410]       12.8     raw water
Friedrich et al 2009a     0.4810 [-0.0580;  1.0200]       12.0     raw water
Friedrich et al 2009b     0.1010 [-1.2749;  1.4769]        9.0  Municipal WW
Goga et al 2019a          4.4000 [ 1.4993;  7.3007]        4.4     raw water
Goga et al 2019b          2.6000 [ 2.5821;  2.6179]       12.8 industrial WW
Pillay et al 2002         0.0940 [-1.2858;  1.4738]        9.0 industrial WW
Ras and von Blottnitz 2012 0.0003 [ 0.0003;  0.0003]      12.8     raw water
Risch et al. 2014         0.2530 [ 0.1059;  0.4001]       12.8  Municipal WW

Number of studies combined: k = 10
Number of observations: o = 20

                      mean           95%-CI
Random effects model 0.7912 [-0.3220; 1.9043]

Quantifying heterogeneity:
 tau^2 = 1.1592 [0.6732; 19.8159]; tau = 1.0766 [0.8205; 4.4515]
 I^2 = 0.0% [0.0%; 62.4%]; H = 1.00 [1.00; 1.63]

Test of heterogeneity:
    Q d.f. p-value
 0.00    9  1.0000

Results for subgroups (random effects model):
                           k   mean              95%-CI  tau^2    tau     Q   I^2
subsource = Municipal WW   4 0.1284 [ -0.5310;  0.7878] 0.0282 0.1678  0.00  0.0%
subsource = raw water      4 0.2036 [ -0.5480;  0.9552] 0.0400 0.1999 32.36 90.7%
subsource = industrial WW  2 1.4459 [-14.4254; 17.3171] 2.8922 1.7006 12.67 92.1%

Test for subgroup differences (random effects model):
                    Q d.f. p-value
Between groups   1.10    2  0.5772

Details on meta-analytical method:
- Inverse variance method
- Restricted maximum-likelihood estimator for tau^2
- Q-profile method for confidence interval of tau^2 and tau
- Hartung-Knapp adjustment for random effects model
- Untransformed (raw) means
```

Figure S7. Subgroup analysis result for global warming potential by water source.

```
Review:     GWP (kg CO2-eq/m^3)

                            mean             95%-CI %W(random) water
Aime et al 2016           8.3300 [ 2.5089; 14.1511]        1.5    WW
Awad et al 2019           0.0000 [ 0.0000;  0.0000]       12.8    WW
Friedrich 2002            0.2380 [ 0.1350;  0.3410]       12.8    RW
Friedrich et al 2009a     0.4810 [-0.0580;  1.0200]       12.0    RW
Friedrich et al 2009b     0.1010 [-1.2749;  1.4769]        9.0    WW
Goga et al 2019a          4.4000 [ 1.4993;  7.3007]        4.4    RW
Goga et al 2019b          2.6000 [ 2.5821;  2.6179]       12.8    WW
Pillay et al 2002         0.0940 [-1.2858;  1.4738]        9.0    WW
Ras and von Blottnitz 2012 0.0003 [ 0.0003;  0.0003]       12.8    RW
Risch et al. 2014         0.2530 [ 0.1059;  0.4001]       12.8    WW

Number of studies combined: k = 10
Number of observations: o = 20

                      mean            95%-CI
Random effects model 0.7912 [-0.3220; 1.9043]

Quantifying heterogeneity:
 tau^2 = 1.1592 [0.6732; 19.8159]; tau = 1.0766 [0.8205; 4.4515]
 I^2 = 0.0% [0.0%; 62.4%]; H = 1.00 [1.00; 1.63]

Test of heterogeneity:
    Q d.f. p-value
 0.00    9  1.0000

Results for subgroups (random effects model):
             k   mean            95%-CI  tau^2    tau        Q    I^2
water = WW   6 0.9196 [-1.0529; 2.8922] 1.6531 1.2857 37239.24 100.0%
water = RW   4 0.2036 [-0.5480; 0.9552] 0.0400 0.1999    32.36  90.7%

Test for subgroup differences (random effects model):
                    Q d.f. p-value
Between groups   0.80    1  0.3725

Details on meta-analytical method:
- Inverse variance method
- Restricted maximum-likelihood estimator for tau^2
- Q-profile method for confidence interval of tau^2 and tau
- Hartung-Knapp adjustment for random effects model
- Untransformed (raw) means
>
```

Figure S8. Subgroup analysis result for global warming potential by water source.

```
Review:     EP (kg PO-eq/m^3)

                            mean             95%-CI %W(random)
Aime et al 2016           0.1829 [ 0.1008; 0.2650]        0.1
Awad et al 2019           0.0000 [ 0.0000; 0.0000]       23.4
Friedrich 2002            0.0001 [ 0.0000; 0.0001]       23.4
Friedrich et al 2009a     0.0002 [-0.0004; 0.0008]       22.9
Friedrich et al 2009b     0.0000 [-0.0296; 0.0296]        0.4
Goga et al 2019a          0.0044 [-0.0844; 0.0933]        0.0
Goga et al 2019b          0.0028 [-0.0253; 0.0309]        0.5
Pillay et al 2002         0.0000 [-0.5692; 0.5693]        0.0
Ras and von Blottnitz 2012 0.0003 [ 0.0003; 0.0003]      23.4
Risch et al. 2014         0.0094 [ 0.0026; 0.0162]        5.9

Number of studies combined: k = 10
Number of observations: o = 20

                      mean            95%-CI
Random effects model 0.0008 [-0.0028; 0.0044]

Quantifying heterogeneity:
 tau^2 < 0.0001 [0.0001; 0.0092]; tau = 0.0020 [0.0096; 0.0960]
 I^2 = 0.0% [0.0%; 62.4%]; H = 1.00 [1.00; 1.63]

Test of heterogeneity:
    Q d.f. p-value
 0.00    9  1.0000

Details on meta-analytical method:
- Inverse variance method
- Restricted maximum-likelihood estimator for tau^2
- Q-profile method for confidence interval of tau^2 and tau
- Hartung-Knapp adjustment for random effects model
- Untransformed (raw) means
```

Figure S9. Result of the pooled mean of eutrophication potential.

```
Review:     EP (kg PO-eq/m^3)

                             mean            95%-CI %W(random)  sublocation
Aime et al 2016            0.1829 [ 0.1008; 0.2650]        0.1       others
Awad et al 2019            0.0000 [ 0.0000; 0.0000]       23.4        Egypt
Friedrich 2002             0.0001 [ 0.0000; 0.0001]       23.4 South Africa
Friedrich et al 2009a      0.0002 [-0.0004; 0.0008]       22.9 South Africa
Friedrich et al 2009b      0.0000 [-0.0296; 0.0296]        0.4 South Africa
Goga et al 2019a           0.0044 [-0.0844; 0.0933]        0.0 South Africa
Goga et al 2019b           0.0028 [-0.0253; 0.0309]        0.5 South Africa
Pillay et al 2002          0.0000 [-0.5692; 0.5693]        0.0 South Africa
Ras and von Blottnitz 2012 0.0003 [ 0.0003; 0.0003]       23.4 South Africa
Risch et al. 2014          0.0094 [ 0.0026; 0.0162]        5.9        Egypt

Number of studies combined: k = 10
Number of observations: o = 20

                       mean            95%-CI
Random effects model 0.0008 [-0.0028; 0.0044]

Quantifying heterogeneity:
 tau^2 < 0.0001 [0.0001; 0.0092]; tau = 0.0020 [0.0096; 0.0960]
 I^2 = 0.0% [0.0%; 62.4%]; H = 1.00 [1.00; 1.63]

Test of heterogeneity:
    Q d.f. p-value
 0.00    9  1.0000

Results for subgroups (random effects model):
                             k   mean            95%-CI   tau^2    tau      Q   I^2
sublocation = others         1 0.1829 [ 0.1008; 0.2650]      --     --   0.00    --
sublocation = Egypt          2 0.0041 [-0.0551; 0.0633] <0.0001 0.0062   5.47 81.7%
sublocation = South Africa   7 0.0002 [ 0.0001; 0.0003] <0.0001 0.0002 209.14 97.1%

Test for subgroup differences (random effects model):
                     Q d.f.  p-value
Between groups   19.71    2 < 0.0001

Details on meta-analytical method:
- Inverse variance method
- Restricted maximum-likelihood estimator for tau^2
- Q-profile method for confidence interval of tau^2 and tau
- Hartung-Knapp adjustment for random effects model
- Untransformed (raw) means
```

Figure S10. Subgroup analysis result for eutrophication potential by location.

```
Review:     EP (kg PO-eq/m^3)

                              mean            95%-CI %W(random)     subsource
Aime et al 2016             0.1829 [ 0.1008; 0.2650]        0.1  Municipal WW
Awad et al 2019             0.0000 [ 0.0000; 0.0000]       23.4  Municipal WW
Friedrich 2002              0.0001 [ 0.0000; 0.0001]       23.4     raw water
Friedrich et al 2009a       0.0002 [-0.0004; 0.0008]       22.9     raw water
Friedrich et al 2009b       0.0000 [-0.0296; 0.0296]        0.4  Municipal WW
Goga et al 2019a            0.0044 [-0.0844; 0.0933]        0.0     raw water
Goga et al 2019b            0.0028 [-0.0253; 0.0309]        0.5 industrial WW
Pillay et al 2002           0.0000 [-0.5692; 0.5693]        0.0 industrial WW
Ras and von Blottnitz 2012 0.0003 [ 0.0003; 0.0003]       23.4     raw water
Risch et al. 2014           0.0094 [ 0.0026; 0.0162]        5.9  Municipal WW

Number of studies combined: k = 10
Number of observations: o = 20

                        mean            95%-CI
Random effects model 0.0008 [-0.0028; 0.0044]

Quantifying heterogeneity:
 tau^2 < 0.0001 [0.0001; 0.0092]; tau = 0.0020 [0.0096; 0.0960]
 I^2 = 0.0% [0.0%; 62.4%]; H = 1.00 [1.00; 1.63]

Test of heterogeneity:
    Q d.f. p-value
 0.00    9  1.0000

Results for subgroups (random effects model):
                            k   mean            95%-CI   tau^2    tau      Q   I^2
subsource = Municipal WW    4 0.0401 [-0.0935; 0.1738]  0.0057 0.0758   0.00  0.0%
subsource = raw water       4 0.0002 [-0.0000; 0.0004] <0.0001 0.0002 209.10 98.6%
subsource = industrial WW   2 0.0028 [ 0.0010; 0.0045]       0      0   0.00  0.0%

Test for subgroup differences (random effects model):
                      Q d.f.  p-value
Between groups   290.18    2 < 0.0001

Details on meta-analytical method:
- Inverse variance method
- Restricted maximum-likelihood estimator for tau^2
- Q-profile method for confidence interval of tau^2 and tau
- Hartung-Knapp adjustment for random effects model
- Untransformed (raw) means
>
```

Figure S11. Subgroup analysis result for eutrophication potential by water source.

```
Review:     EP (kg PO-eq/m^3)

                             mean            95%-CI %W(random) water
Aime et al 2016            0.1829 [ 0.1008; 0.2650]        0.1    WW
Awad et al 2019            0.0000 [ 0.0000; 0.0000]       23.4    WW
Friedrich 2002             0.0001 [ 0.0000; 0.0001]       23.4    RW
Friedrich et al 2009a      0.0002 [-0.0004; 0.0008]       22.9    RW
Friedrich et al 2009b      0.0000 [-0.0296; 0.0296]        0.4    WW
Goga et al 2019a           0.0044 [-0.0844; 0.0933]        0.0    RW
Goga et al 2019b           0.0028 [-0.0253; 0.0309]        0.5    WW
Pillay et al 2002          0.0000 [-0.5692; 0.5693]        0.0    WW
Ras and von Blottnitz 2012 0.0003 [ 0.0003; 0.0003]       23.4    RW
Risch et al. 2014          0.0094 [ 0.0026; 0.0162]        5.9    WW

Number of studies combined: k = 10
Number of observations: o = 20

                       mean            95%-CI
Random effects model 0.0008 [-0.0028; 0.0044]

Quantifying heterogeneity:
 tau^2 < 0.0001 [0.0001; 0.0092]; tau = 0.0020 [0.0096; 0.0960]
 I^2 = 0.0% [0.0%; 62.4%]; H = 1.00 [1.00; 1.63]

Test of heterogeneity:
    Q d.f. p-value
 0.00    9  1.0000

Results for subgroups (random effects model):
             k   mean            95%-CI   tau^2    tau      Q   I^2
water = WW   6 0.0294 [-0.0438; 0.1027]  0.0036 0.0603   0.00  0.0%
water = RW   4 0.0002 [-0.0000; 0.0004] <0.0001 0.0002 209.10 98.6%

Test for subgroup differences (random effects model):
                    Q d.f. p-value
Between groups   1.05    1  0.3048

Details on meta-analytical method:
- Inverse variance method
- Restricted maximum-likelihood estimator for tau^2
- Q-profile method for confidence interval of tau^2 and tau
- Hartung-Knapp adjustment for random effects model
- Untransformed (raw) means
```

Figure S12. Subgroup analysis result for eutrophication potential by water source.

S4. List of articles selected for this review

H. Awad, M. Gar Alalm, H. K. El-Etriby, *Sci. Total Environ.* **2019**, *660*, 57–68. DOI: 10.1016/j.scitotenv.2018.12.386.

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V. Masindi, E. Chatzisymeon, I. Kortidis, S. Foteinis, *Sci. Total Environ*. **2018**, *635*, 793–802. DOI: 10.1016/j.scitotenv.2018.04.108.

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Appendix B

Supplementary Information

Techno-economic analysis of electricity generation from household sewage sludge in different regions of Nigeria

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Table S1 Calculation of population.

Zones	State	Base Population in 2006 (NBS, 2023)	Annual growth rate (%) (NBS, 2023)	Estimated 2022 population	Estimated 20-yr average population
SE	Abia	2,845,380	2.7	4,382,838.73	5,818,403.56
NE	Adamawa	3,178,950	2.9	5,055,875.10	6,861,470.69
SS	Akwa-Ibom	3,902,051	3.4	6,722,783.72	9,646,605.86
SE	Anambra	4,177,828	2.8	6,539,047.38	8,776,902.44
NE	Bauchi	4,653,066	3.4	8,016,695.92	11,503,256.56
SS	Bayelsa	1,704,515	2.9	2,710,899.81	3,679,038.59
NC	Benue	4,253,641	3	6,874,200.34	9,433,064.02
NE	Borno	4,171,104	3.4	7,186,331.00	10,311,755.61
SS	Cross River	2,892,988	2.9	4,601,074.57	6,244,248.06
SS	Delta	4,112,445	3.2	6,862,128.99	9,628,435.68
SE	Ebonyi	2,176,947	2.8	3,407,311.07	4,573,393.50
SS	Edo	3,233,366	2.7	4,980,467.19	6,611,780.58
SW	Ekiti	2,398,957	3.1	3,939,422.19	5,466,237.00
SE	Enugu	3,267,837	3	5,281,067.73	7,246,901.10
NE	Gombe	2,365,040	3.2	3,946,365.13	5,537,249.87
SE	Imo	3,927,563	3.2	6,553,630.24	9,195,572.89
NW	Jigawa	4,361,002	2.9	6,935,837.75	9,412,821.03
NW	Kaduna	6,113,503	3	9,879,875.71	13,557,576.95
NW	Kano	9,401,288	3.3	15,940,239.54	22,617,687.29
NW	Katsina	5,801,584	3	9,375,791.39	12,865,851.47

Table S1 Calculation of population contd.

Zones	State	Base Population in 2006 (NBS, 2023)	Annual growth rate (%) (NBS, 2023)	Estimated 2022 population	Estimated 20-yr average population
NW	Kebbi	3,256,541	3.1	5,347,694.80	7,420,318.46
NC	Kogi	3,314,043	3	5,355,740.06	7,349,369.58
NC	Kwara	2,365,353	3	3,822,586.44	5,245,512.32
SW	Lagos	9,113,605	3.2	15,207,190.15	21,337,612.93
NC	Nasarawa	1,869,377	3	3,021,052.32	4,145,613.82
NC	Niger	3,954,772	3.4	6,813,615.92	9,776,942.11
SW	Ogun	3,751,140	3.3	6,360,199.81	9,024,519.99
SW	Ondo	3,460,877	3	5,593,034.73	7,674,995.21
SW	Osun	3,416,959	3.2	5,701,623.59	8,000,099.69
SW	Oyo	5,580,894	3.4	9,615,236.53	13,797,022.33
NC	Plateau	3,206,531	2.7	4,939,132.30	6,556,906.77
SS	Rivers	5,198,716	3.4	8,956,787.92	12,852,206.25
NW	Sokoto	3,702,676	3	5,983,799.90	8,211,219.46
NE	Taraba	2,294,800	2.9	3,649,702.63	4,953,114.37
NE	Yobe	2,321,339	3.5	4,063,904.35	5,897,343.73
NW	Zamfara	3,278,873	3.2	5,471,209.82	7,676,800.01
NC	FCT Abuja	1,406,239	9.3	6,227,150.00	18,406,757.53
NATIONAL	Nigeria	140,431,790	3.2	234,328,011.06	328,791,864.24

Table S2 Estimation of wastewater generation and collection.

Zone	State	V_{WA}*	Wastewater generation (L) 2022	Wastewater generation (L) 20-yr average	WW_{CR}*	Wastewater collection (L) 2022	Wastewater collection (L) 20-yr average
SE	Abia	11	15,837,387,750.77	21,024,801,256.01	13.6	2,153,884,734.11	2,859,372,970.82
NE	Adamawa	9	14,947,694,738.71	20,285,938,094.59	13.9	2,077,729,568.68	2,819,745,395.15
SS	Akwa-Ibom	12	26,501,213,411.75	38,026,920,302.22	0	0.00	0.00
SE	Anambra	9	19,332,693,578.10	25,948,912,049.13	0.1	19,332,693.58	25,948,912.05
NE	Bauchi	6	15,800,907,661.76	22,672,918,670.58	5.9	932,253,552.04	1,337,702,201.56
SS	Bayelsa	11	9,795,836,461.48	13,294,205,930.48	2.4	235,100,075.08	319,060,942.33
NC	Benue	10	22,581,748,104.48	30,987,615,310.37	0.6	135,490,488.63	185,925,691.86
NE	Borno	12	28,328,516,789.40	40,648,940,616.17	9.2	2,606,223,544.62	3,739,702,536.69
SS	Cross River	6	9,068,717,974.33	12,307,412,924.89	2.2	199,511,795.44	270,763,084.35
SS	Delta	10	22,542,093,735.66	31,629,411,225.14	0	0.00	0.00
SE	Ebonyi	5	5,596,508,425.85	7,511,798,826.06	0.7	39,175,558.98	52,582,591.78
SS	Edo	10	16,360,834,719.05	21,719,699,218.30	5.4	883,485,074.83	1,172,863,757.79
SW	Ekiti	5	6,470,500,942.49	8,978,294,274.99	0	0.00	0.00
SE	Enugu	8	13,878,645,984.56	19,044,856,085.03	15.6	2,165,068,773.59	2,970,997,549.27
NE	Gombe	8	10,371,047,562.91	14,551,892,652.45	0	0.00	0.00
SE	Imo	12	25,834,410,419.70	36,248,948,323.34	15.4	3,978,499,204.63	5,582,338,041.79
NW	Jigawa	14	31,897,917,834.95	43,289,563,899.79	0.6	191,387,507.01	259,737,383.40
NW	Kaduna	14	45,437,548,372.03	62,351,296,413.57	5	2,271,877,418.60	3,117,564,820.68
NW	Kano	5	26,181,843,452.65	37,149,551,371.79	0.2	52,363,686.91	74,299,102.74
NW	Katsina	9	27,719,527,258.05	38,037,889,860.60	0.2	55,439,054.52	76,075,779.72

Table S2 Estimation of wastewater generation and collection contd.

Zone	State	V_{WA}*	Wastewater generation (L) 2022	Wastewater generation (L) 20-yr average	WW_{CR}*	Wastewater collection (L) 2022	Wastewater collection (L) 20-yr average
NW	Kebbi	5	8,783,588,705.32	12,187,873,070.07	0	0.00	0.00
NC	Kogi	13	22,871,687,926.51	31,385,482,810.57	2.7	617,535,574.02	847,408,035.89
NC	Kwara	8	10,045,757,152.36	13,785,206,384.31	1.2	120,549,085.83	165,422,476.61
SW	Lagos	9	44,960,057,669.29	63,084,652,623.83	7.4	3,327,044,267.53	4,668,264,294.16
NC	Nasarawa	12	11,908,988,236.56	16,342,009,684.24	0.1	11,908,988.24	16,342,009.68
NC	Niger	12	26,859,273,947.68	38,540,705,812.77	8	2,148,741,915.81	3,083,256,465.02
SW	Ogun	14	29,250,558,933.75	41,503,767,438.23	0	0.00	0.00
SW	Ondo	6	11,023,871,450.54	15,127,415,564.10	5.7	628,360,672.68	862,262,687.15
SW	Osun	6	11,237,900,091.39	15,768,196,489.01	6.3	707,987,705.76	993,396,378.81
SW	Oyo	8	25,268,841,595.07	36,258,574,674.89	1.8	454,839,148.71	652,654,344.15
NC	Plateau	11	17,847,554,555.76	23,693,382,604.87	2.8	499,731,527.56	663,414,712.94
SS	Rivers	14	41,192,267,659.64	59,107,296,523.50	26.7	10,998,335,465.12	15,781,648,171.78
NW	Sokoto	11	21,622,460,950.26	29,671,241,521.71	3.2	691,918,750.41	949,479,728.69
NE	Taraba	9	10,790,345,833.18	14,643,882,646.62	0.2	21,580,691.67	29,287,765.29
NE	Yobe	14	18,689,896,111.01	27,121,883,808.25	0.2	37,379,792.22	54,243,767.62
NW	Zamfara	6	10,783,754,556.72	15,130,972,811.36	0	0.00	0.00
NC	FCT Abuja	15	30,684,281,639.46	90,699,297,721.52	15.6	4,786,747,935.76	14,149,090,444.56

*WW_{CR} = wastewater collection rate (%), V_{WA} = water accessibility (l/c/d) (FMWR et al., 2022).

Table S3 Estimation of sludge production for AD and INC.

Zone	State	WW_{CR}*	Sewage Sludge for AD (t) 2022	Sewage Sludge for AD (t) 20-Year Average	Sewage Sludge for INC (t) 2022	Sewage Sludge for INC (t) 20-Year Average
SE	Abia	13.6	21538.84734	28593.72971	904.6315883	1200.936648
NE	Adamawa	13.9	20777.29569	28197.45395	872.6464188	1184.293066
SS	Akwa/ibom	0	0	0	0	0
SE	Anambra	0.1	193.3269358	259.4891205	8.119731303	10.89854306
NE	Bauchi	5.9	9322.53552	13377.02202	391.5464919	561.8349247
SS	Bayelsa	2.4	2351.000751	3190.609423	98.74203153	134.0055958
NC	Benue	0.6	1354.904886	1859.256919	56.90600522	78.08879058
NE	Borno	9.2	26062.23545	37397.02537	1094.613889	1570.675065
SS	Cross river	2.2	1995.117954	2707.630843	83.79495408	113.7204954
SS	Delta	0	0	0	0	0
SE	Ebonyi	0.7	391.7555898	525.8259178	16.45373477	22.08468855
SS	Edo	5.4	8834.850748	11728.63758	371.0637314	492.6027783
SW	Ekiti	0	0	0	0	0
SE	Enugu	15.6	21650.68774	29709.97549	909.3288849	1247.818971
NE	Gombe	0	0	0	0	0
SE	Imo	15.4	39784.99205	55823.38042	1670.969666	2344.581978
NW	Jigawa	0.6	1913.87507	2597.373834	80.38275294	109.089701
NW	Kaduna	5	22718.77419	31175.64821	954.1885158	1309.377225
NW	Kano	0.2	523.6368691	742.9910274	21.9927485	31.20562315
NW	Katsina	0.2	554.3905452	760.7577972	23.2844029	31.95182748

Table S3 Estimation of sludge production for AD and INC contd.

Zone	State	WW_{CR}*	Sewage Sludge for AD (t)		Sewage Sludge for INC (t)	
			2022	20-Year Average	2022	20-Year Average
NW	Kebbi	0	0	0	0	0
NC	Kogi	2.7	6175.35574	8474.080359	259.3649411	355.9113751
NC	Kwara	1.2	1205.490858	1654.224766	50.63061605	69.47744018
SW	Lagos	7.4	33270.44268	46682.64294	1397.358592	1960.671004
NC	Nasarawa	0.1	119.0898824	163.4200968	5.001775059	6.863644067
NC	Niger	8	21487.41916	30832.56465	902.4716046	1294.967715
SW	Ogun	0	0	0	0	0
SW	Ondo	5.7	6283.606727	8622.626872	263.9114825	362.1503286
SW	Osun	6.3	7079.877058	9933.963788	297.3548364	417.2264791
SW	Oyo	1.8	4548.391487	6526.543441	191.0324425	274.1148245
NC	Plateau	2.8	4997.315276	6634.147129	209.8872416	278.6341794
SS	Rivers	26.7	109983.3547	157816.4817	4619.300895	6628.292232
NW	Sokoto	3.2	6919.187504	9494.797287	290.6058752	398.7814861
NE	Taraba	0.2	215.8069167	292.8776529	9.0638905	12.30086142
NE	Yobe	0.2	373.7979222	542.4376762	15.69951273	22.7823824
NW	Zamfara	0	0	0	0	0
NC	FCT Abuja	15.6	47867.47936	141490.9044	2010.434133	5942.617987

*WW_{CR} = wastewater collection rate (%), (FMWR et al., 2022).

Result of Sensitivity Analysis

The results of the sensitivity analyses are displayed in this section from Figure S1 – S10.

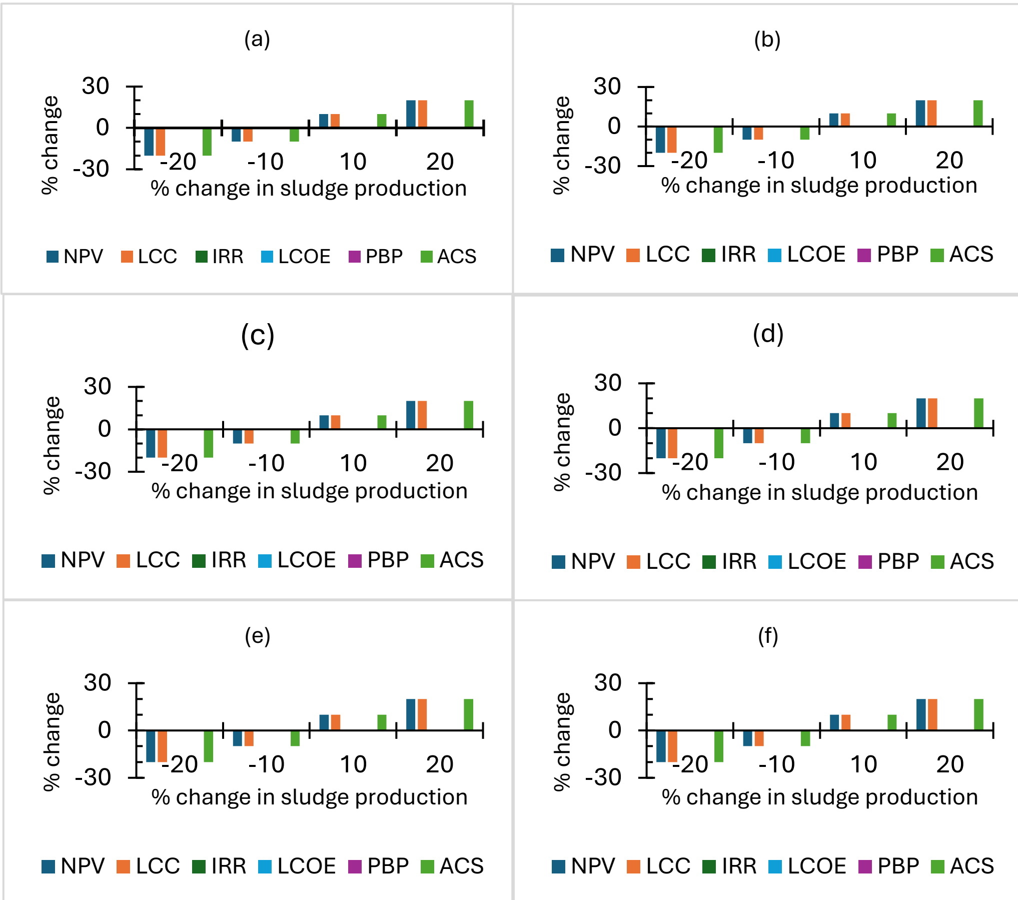

Figure S1 Sensitivity Analysis: Change in sludge production for AD technology for (a) NC (b) NE (c) NW (d) SE (e) SS (d) SW.

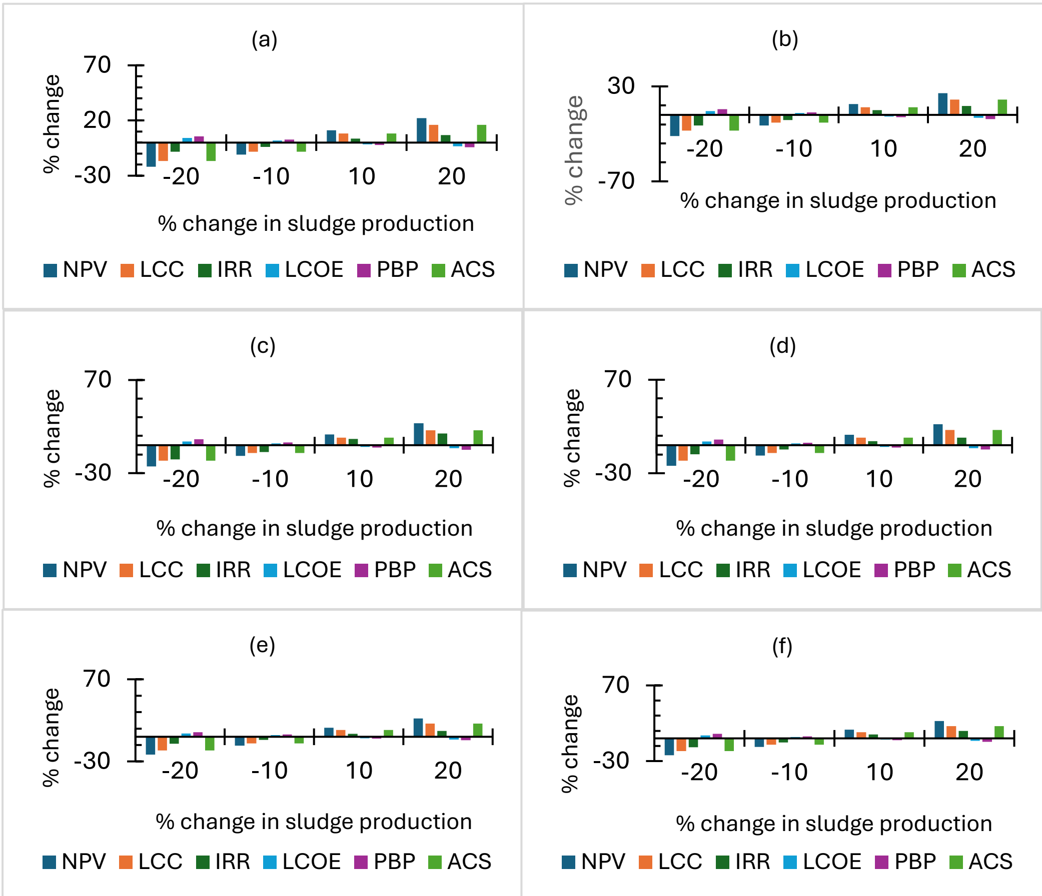

Figure S2 Sensitivity Analysis: Change in sludge production for INC technology for (a) NC (b) NE (c) NW (d) SE (e) SS (d) SW.

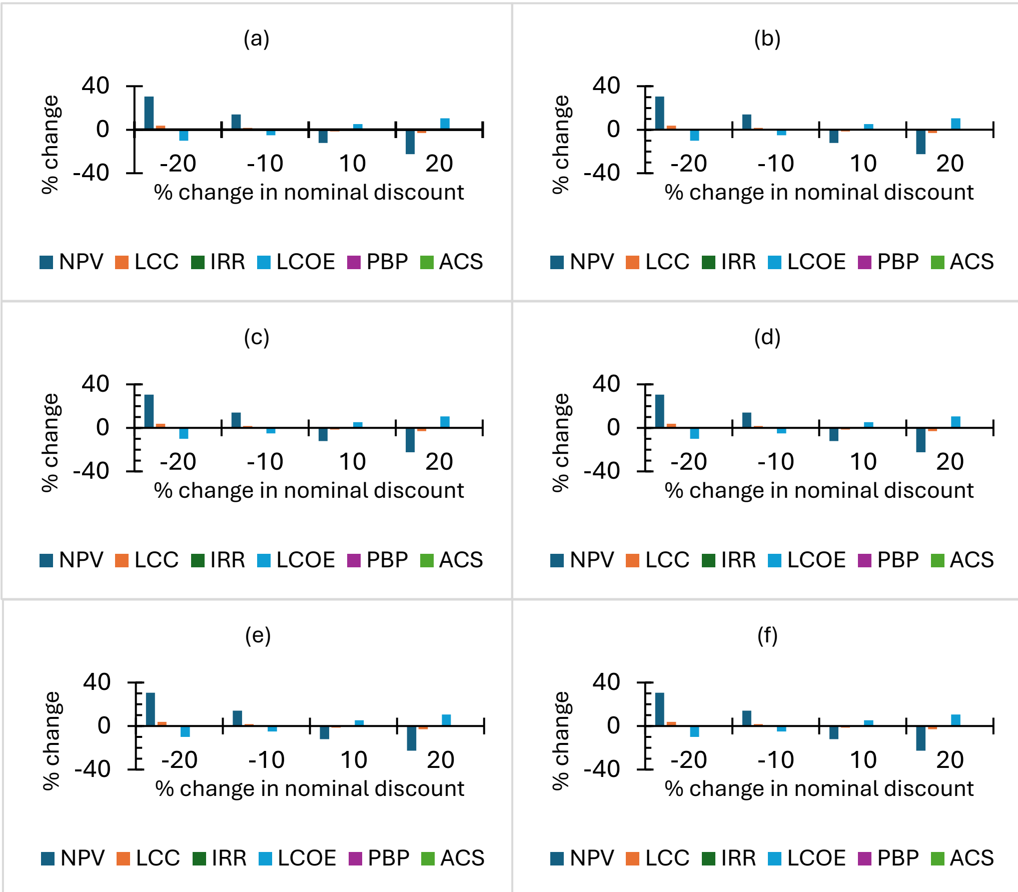

Figure S3 Sensitivity Analysis: Change in Nominal discount rate for AD technology for (a) NC (b) NE (c) NW (d) SE (e) SS (d) SW.

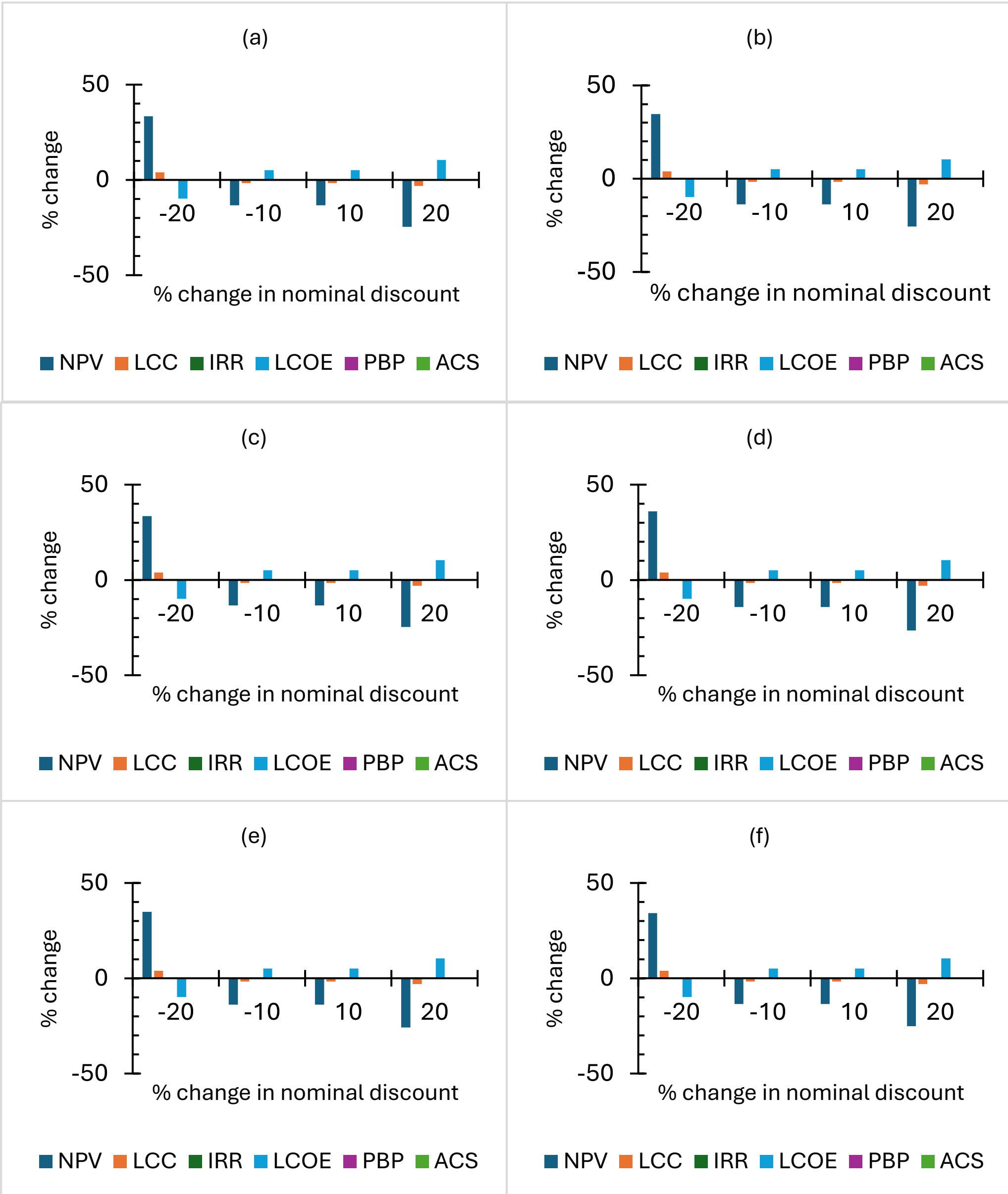

Figure S4 Sensitivity Analysis: Change in Nominal discount rate for INC technology for (a) NC (b) NE (c) NW (d) SE (e) SS (d) SW.

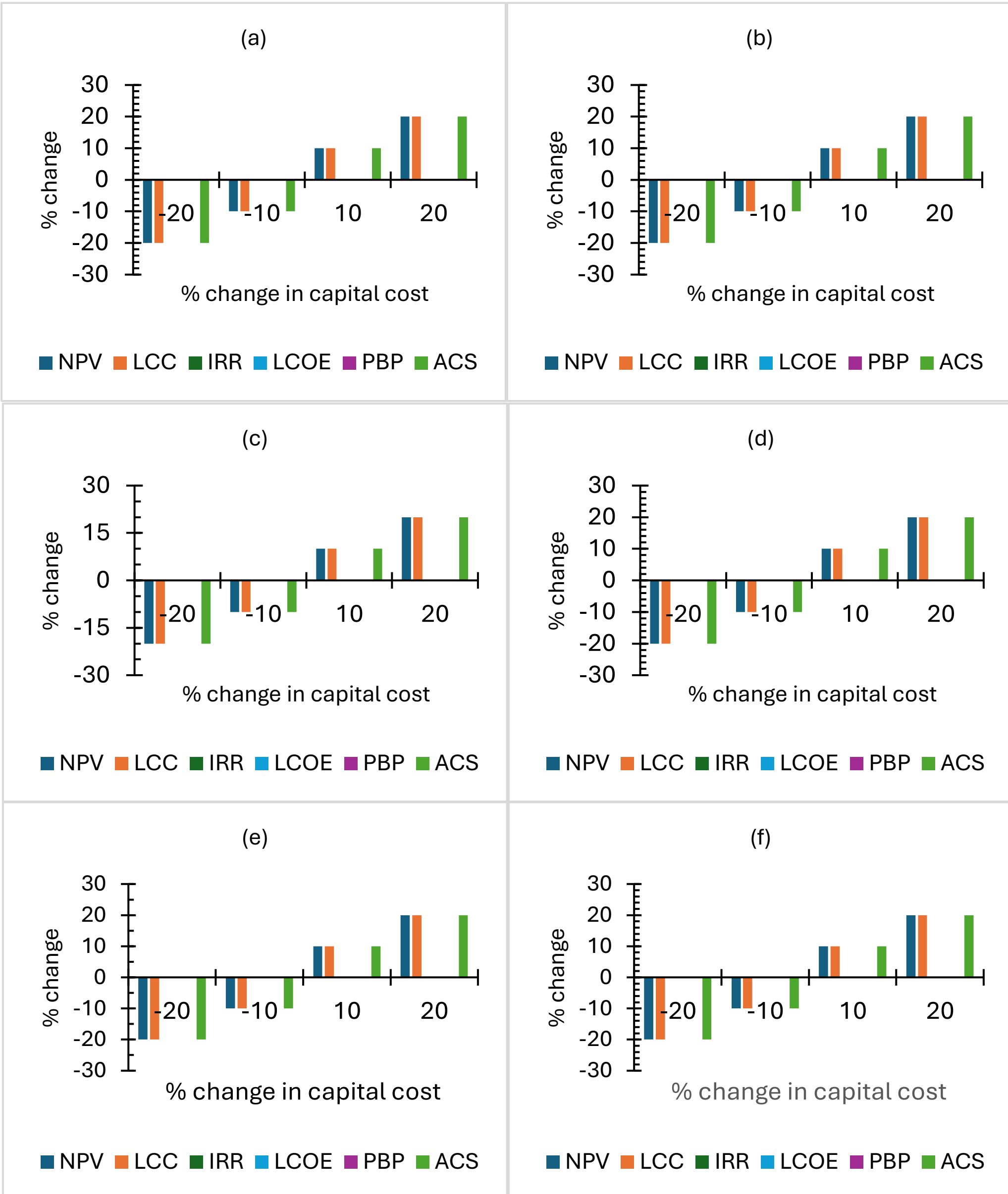

Figure S5 Sensitivity Analysis: Change in capital cost for AD technology for (a) NC (b) NE (c) NW (d) SE (e) SS (d) SW.

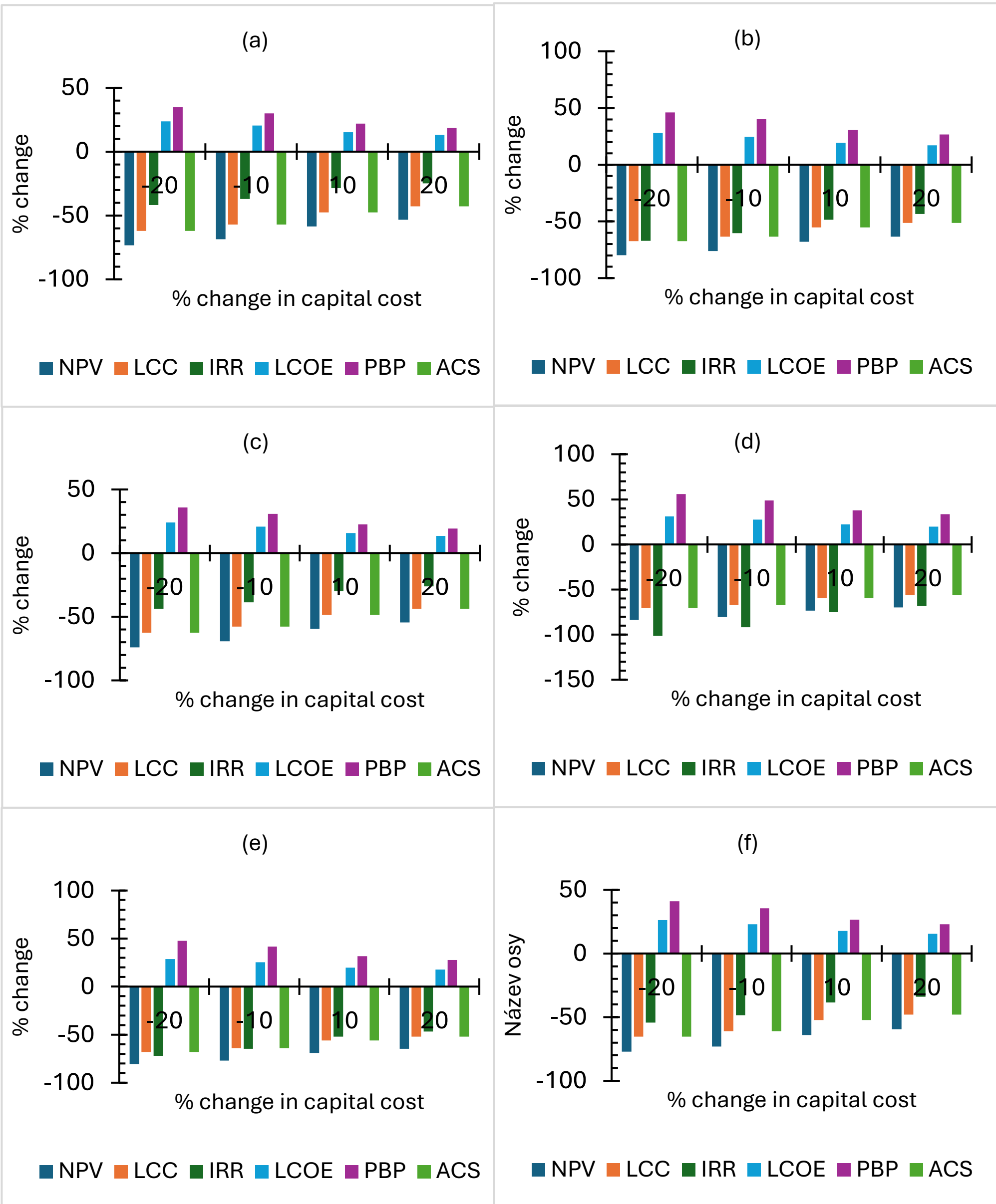

Figure S6 Sensitivity Analysis: Change in capital cost for INC technology for (a) NC (b) NE (c) NW (d) SE (e) SS (d) SW.

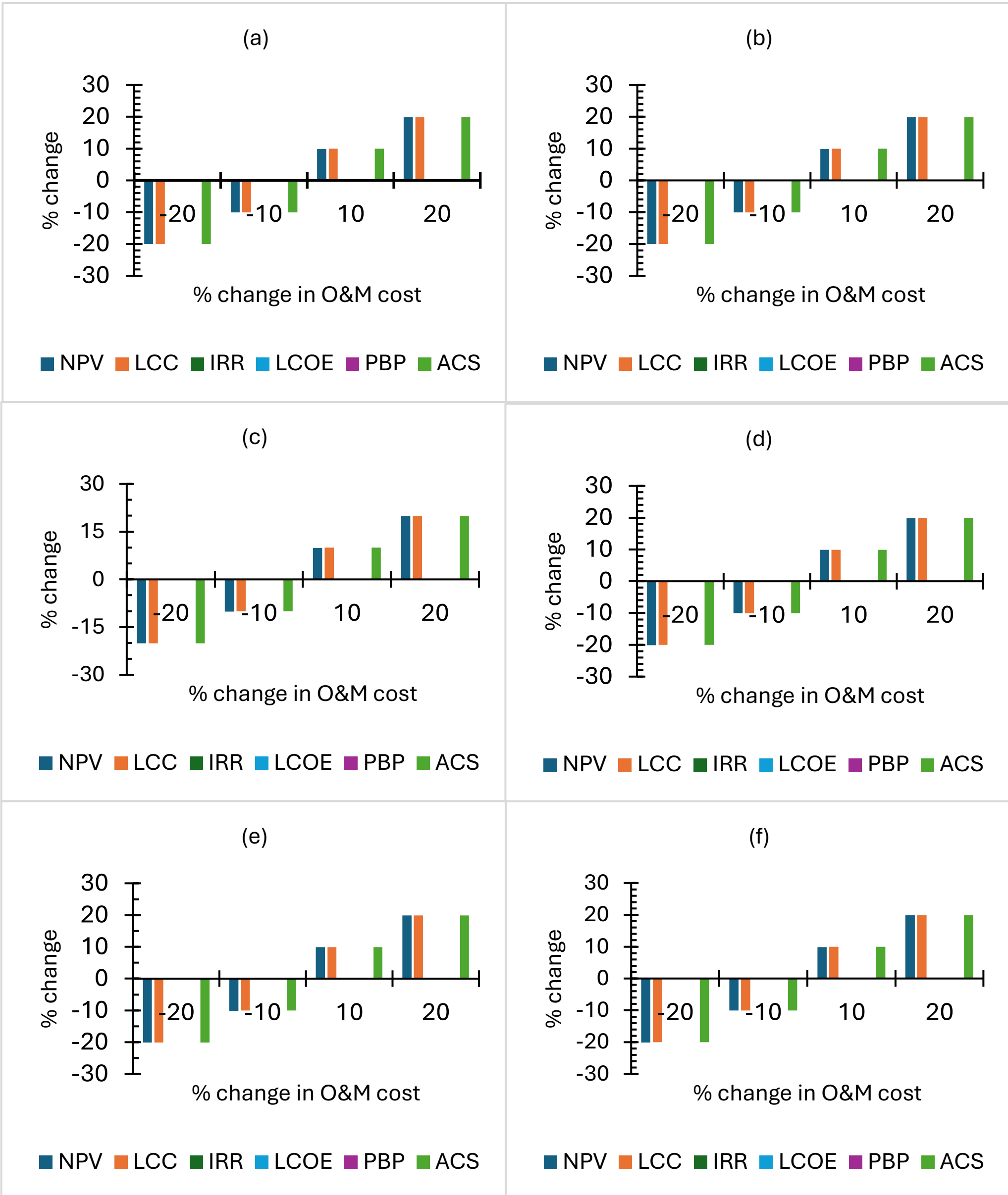

Figure S7 Sensitivity Analysis: Change in O&M cost for AD technology for (a) NC (b) NE (c) NW (d) SE (e) SS (d) SW.

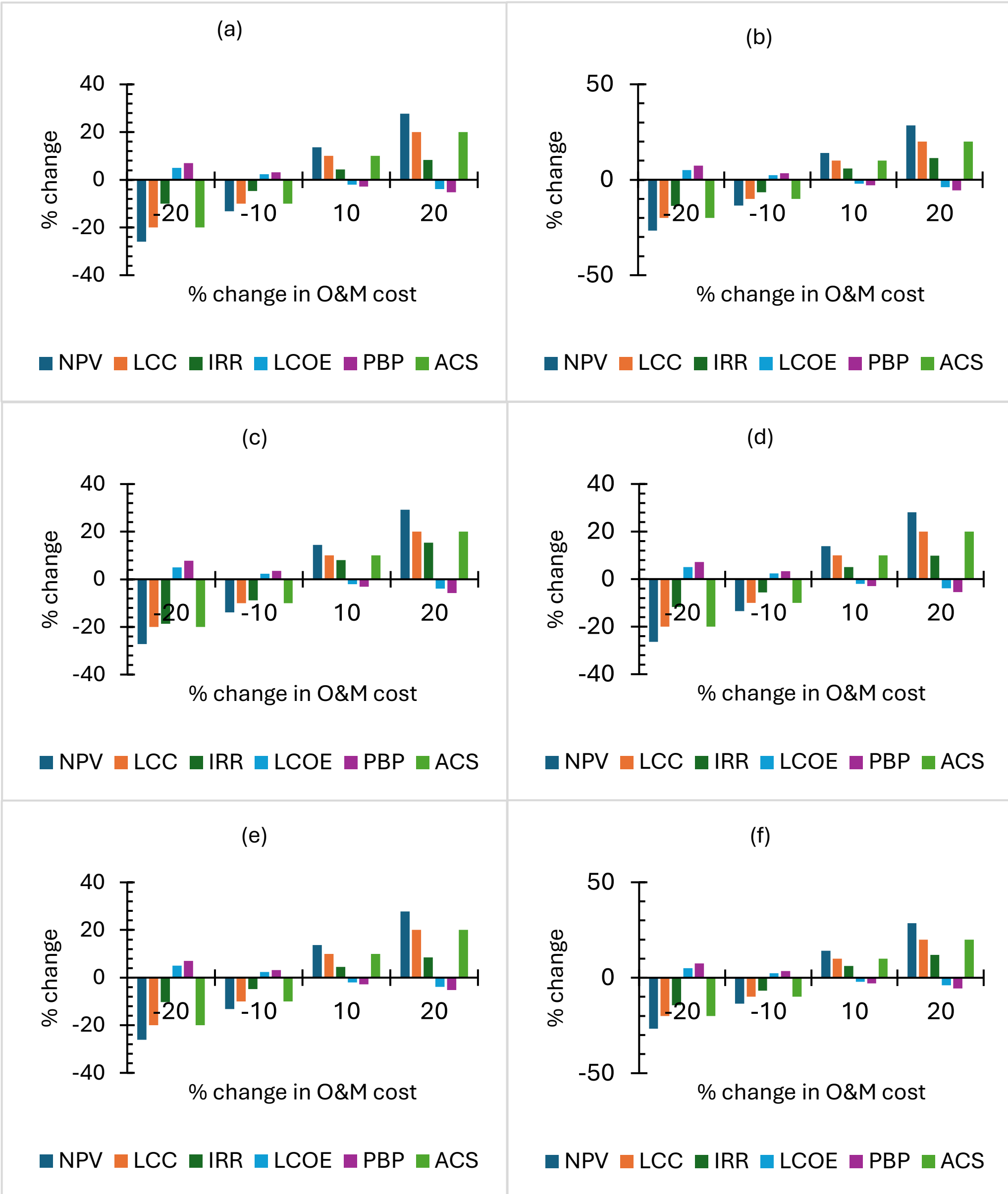

Figure S8 Sensitivity Analysis: Change in O&M cost for INC technology for (a) NC (b) NE (c) NW (d) SE (e) SS (d) SW.

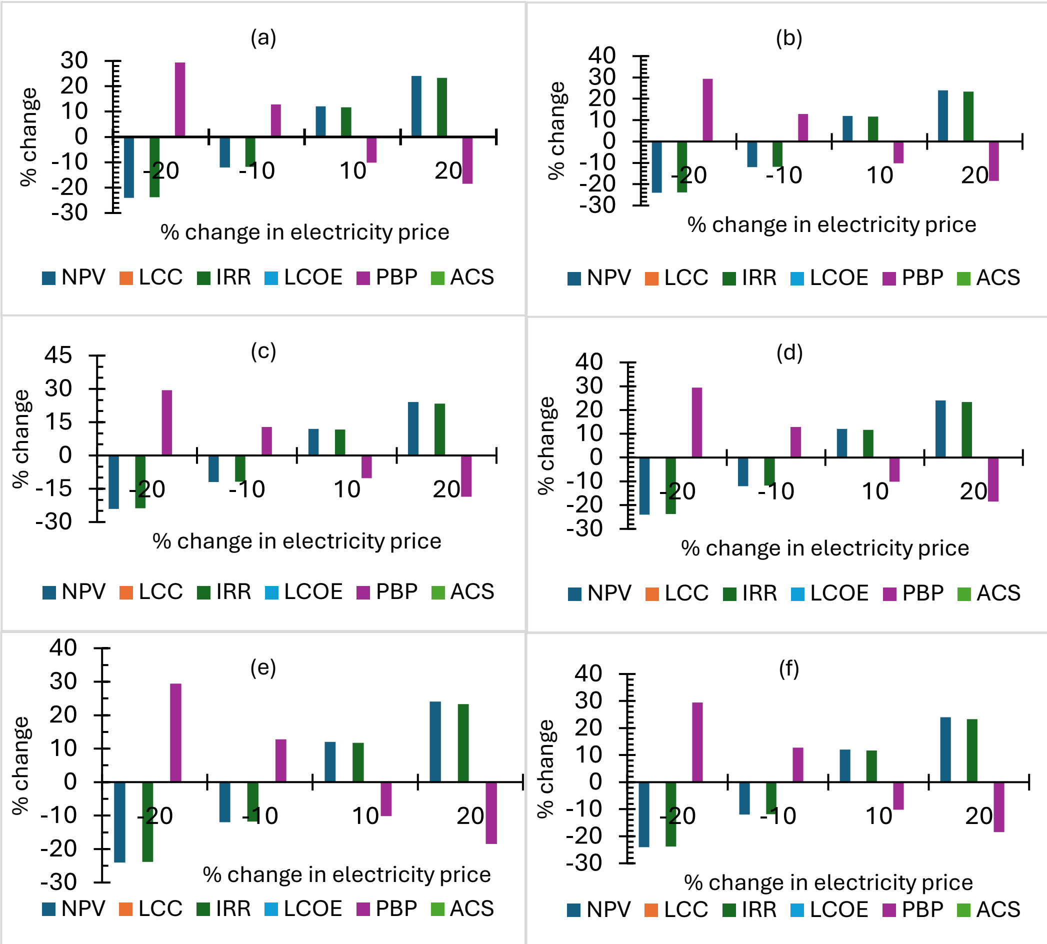

Figure S9 Sensitivity Analysis: Change in electricity selling price for AD technology for (a) NC (b) NE (c) NW (d) SE (e) SS (d) SW.

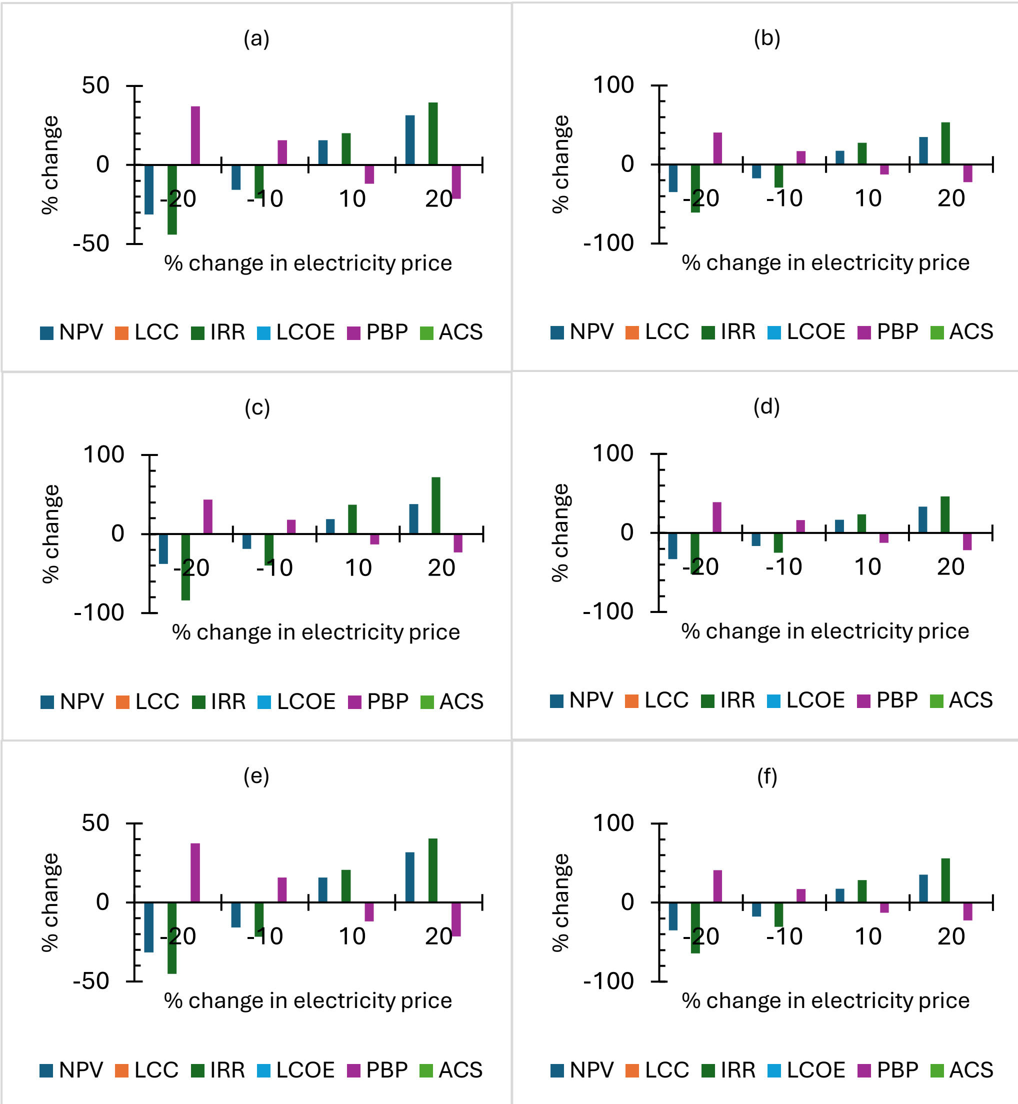

Figure S10 Sensitivity Analysis: Change in electricity selling price for INC technology for (a) NC (b) NE (c) NW (d) SE (e) SS (d) SW.

Appendix C

Evaluation of Treatment Efficiency, Effluent Quality Indices, and Greenhouse Gas Emissions of a Wastewater Treatment Plant in Abuja, Nigeria.

S1. Water Quality

Table S1 Pearson correlation coefficients of REs.

	pH	DO	NO_3-N	NO_2-N	NH_4-N	PO_4	Cl^-	SO_4	Fe^{2+}	BOD	TSS	COD	TCC	FCC
pH	1													
DO	0.041702	1												
NO_3-N	-0.13779	-0.17709	1											
NO_2-N	0.081319	0.023568	0.053758	1										
NH_4-N	-0.00357	-0.02496	-0.03195	-0.06827	1									
PO_4	0.222481	0.190335	0.038946	0.02118	0.235376	1								
Cl^-	0.084462	-0.02704	0.097157	-0.07842	-0.17795	0.029036	1							
SO_4	0.028115	0.124204	0.020033	0.150999	-0.26203	0.106145	-0.21099	1						
Fe^{2+}	0.018552	0.089071	-0.13691	-0.04415	0.186615	-0.11181	-0.01938	0.018081	1					
BOD	0.292189	0.014267	-0.0596	-0.15618	0.105253	0.038496	0.106033	-0.27123	-0.04304	1				
TSS	0.211264	0.011934	-0.22003	-0.01769	-0.10932	-0.1062	0.164933	-0.07213	-0.10706	0.490234	1			
COD	0.202788	-0.18669	-0.01382	-0.07652	-0.12839	-0.16156	0.060785	-0.10073	-0.06126	0.515131	0.593823	1		
TCC	-0.02154	0.235418	-0.10684	0.005012	-0.03615	0.074784	0.046262	0.002803	0.416789	0.112302	0.105826	0.013293	1	
FCC	0.0546	0.276	-0.06014	-0.02167	-0.06109	-0.12104	0.022305	-0.11152	0.020244	0.250695	0.346607	0.156764	0.208378	1

Table S2 Correlation matrix of the scores of the extracted PCs.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
PC1	1.00E+00	5.24E-17	8.13E-17	-1.16E-16	-7.19E-18	-1.63E-16	-5.47E-17
PC2	5.24E-17	1.00E+00	-2.90E-17	-5.67E-16	-2.63E-16	8.54E-16	-8.60E-17
PC3	8.13E-17	-2.90E-17	1.00E+00	2.26E-16	2.64E-16	1.22E-16	-9.91E-17
PC4	-1.16E-16	-5.67E-16	2.26E-16	1.00E+00	-5.63E-17	1.10E-16	2.28E-16
PC5	-7.19E-18	-2.63E-16	2.64E-16	-5.63E-17	1.00E+00	-5.16E-16	1.40E-16
PC6	-1.63E-16	8.54E-16	1.22E-16	1.10E-16	-5.16E-16	1.00E+00	-3.18E-16
PC7	-5.47E-17	-8.60E-17	-9.91E-17	2.28E-16	1.40E-16	-3.18E-16	1.00E+00

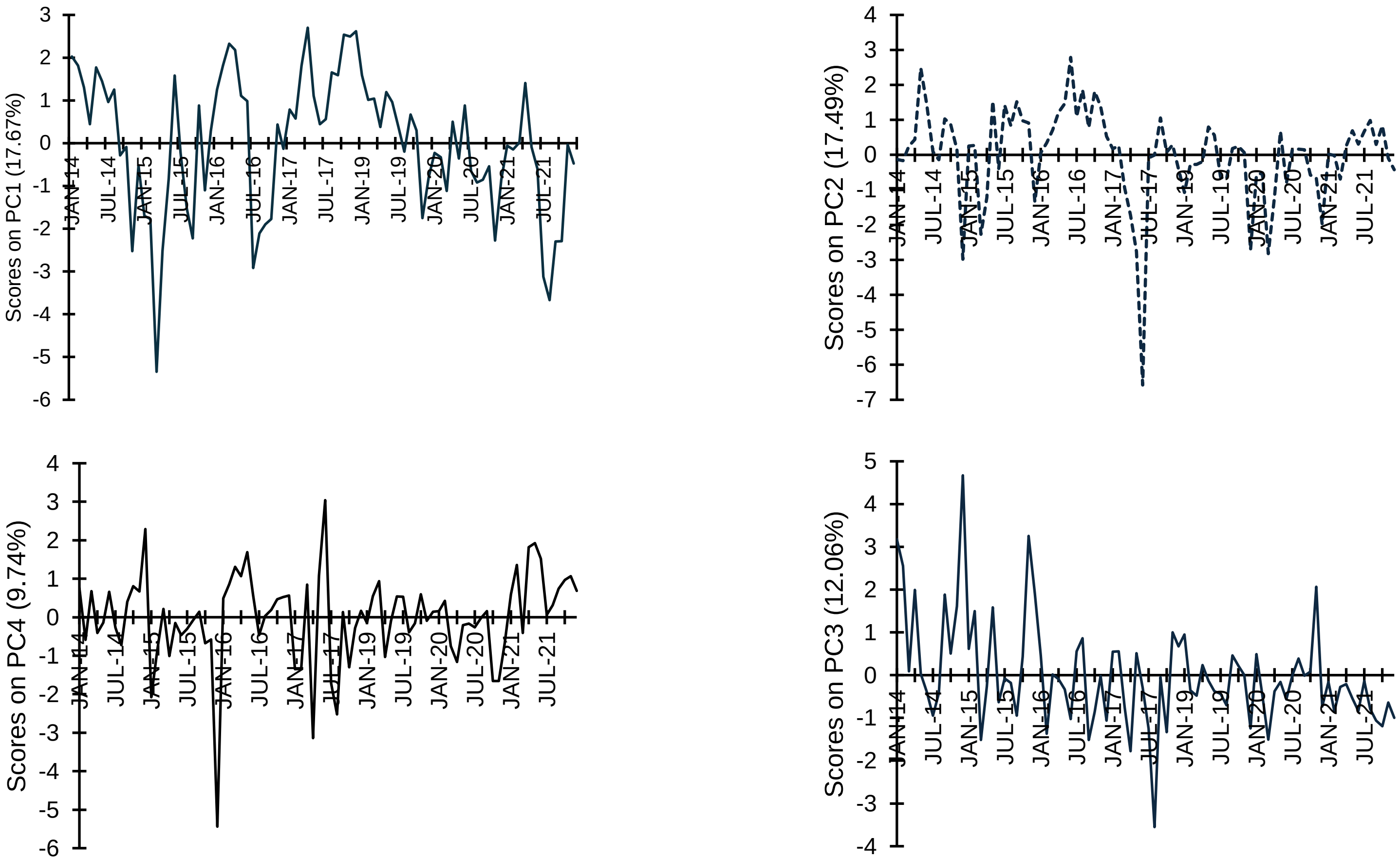

Figure S1 Temporal variation of the principal components scores.

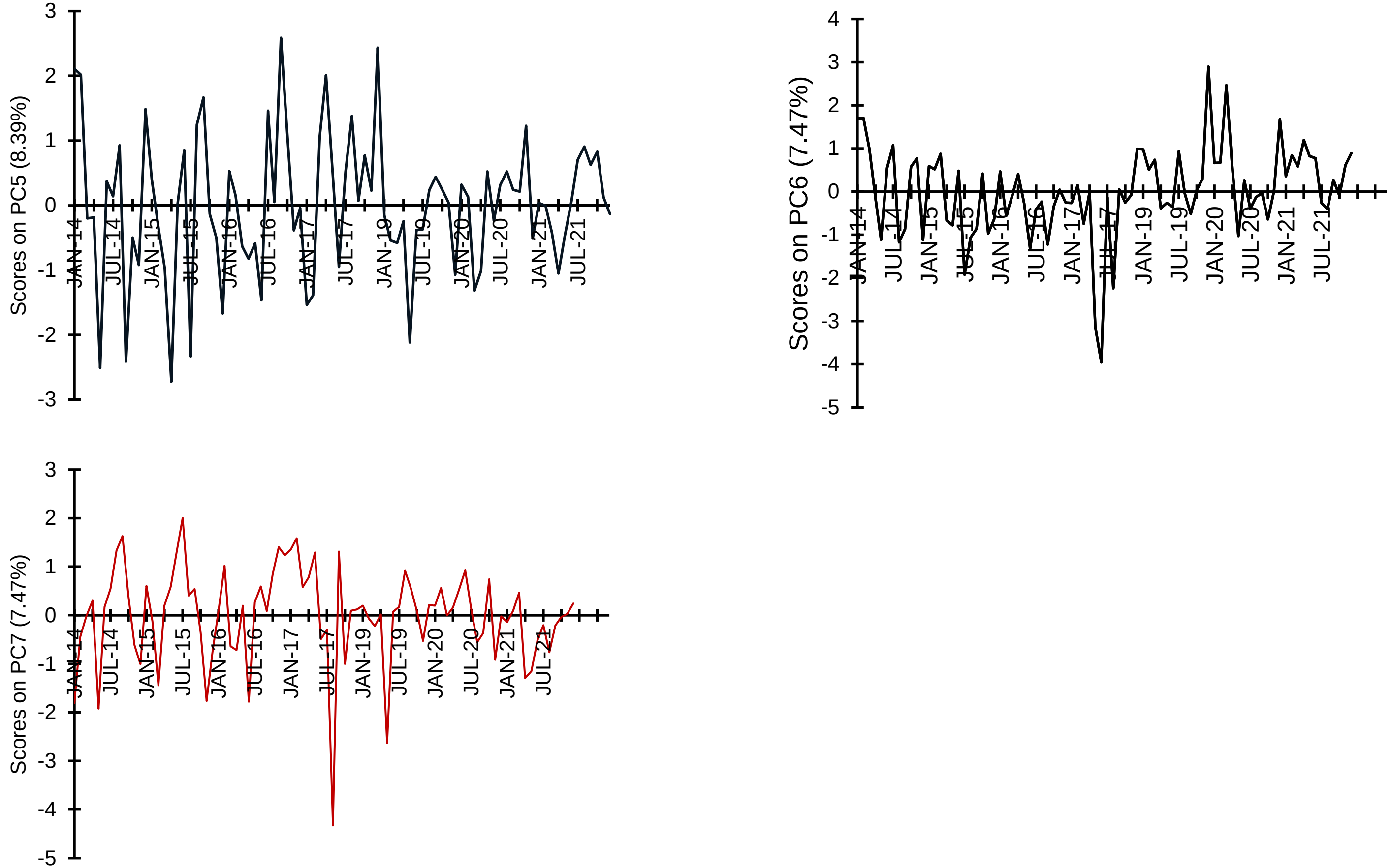

Figure S1 Temporal variation of the principal components scores contd.

Table S3 Limits of water quality parameters considered in this study.

Parameter	Units	Limits	Source
pH	unitless	5.5-9	NESREA (2009)
TSS	mg/l	100	NESREA (2009)
DO	mg/l	min. 4	(FAO, 2003)
BOD_5	mg/l	30	NESREA (2009)
COD	mg/l	250	NESREA (2009)
NH_4-N	mg/l	50	NESREA (2009)
NO_2-N	mg/l	10	NESREA (2011)
NO_3-N	mg/l	10	(FAO, 2003)
PO_4	mg/l	5	NESREA (2011)
Cl^-	mg/l	600	NESREA (2011)
SO_4^{2-}	mg/l	500	NESREA (2011)
Fe^{2+}	mg/l	20	NESREA (2011)
TCC	MPN per 100 ml	400	(FAO, 2003)
FCC	MPN per 100 ml	200	(FAO, 2003)

Table S4 Average effluent concentration of water quality parameters.

	Year																				
	2014			2015			2016			2017			2019			2020			2021		
	n	mean	SD	n	mean	SD	n	mean	SD	n	mean	SD	n	mean	SD	n	mean	SD	n	mean	SD
pH	12	7.08	0.15	12	7.3	0.12	12	7.1	0.23	12	7	0.22	12	7.08	0.14	12	7.17	0.128794	12	6.99	0.11
DO	12	6.57	0.71	12	6.8	0.32	12	6.9	0.12	12	6.64	0.37	12	6.8	0.2	12	6.83	0.285321	12	6.95	0.12
NO_3-N	12	5.45	3.69	12	5.71	1.99	12	7.5	1.95	12	6.03	1.62	12	6.08	3.92	12	4.98	1.962362	12	8.67	3.37
NO_2-N	12	0.18	0.24	12	0.22	0.13	12	0.4	0.57	12	0.79	1.46	-	-	-	-	-	-	-	-	-
NH_4-N	12	3.08	3.29	12	3.19	2.4	12	1.4	1.09	12	1.44	0.57	12	2.3	1.79	12	3.1	1.953549	12	2.62	1.81
PO_4	12	1.64	0.29	12	1.91	0.61	12	2.1	0.71	12	1.52	0.67	12	1.77	0.31	12	1.53	0.642592	12	2.18	0.74
Cl^-	12	32.8	8.92	12	35	4.57	12	32	5.56	12	30.3	10.1	-	-	-	-	-	-	-	-	-
FCC	12	33.5	39.2	12	43.2	77.1	12	15	8.81	12	9.25	4.9	12	69.4	40.8	12	97.25	69.73994	12	128.3	39.4
TCC	12	71.2	71.7	12	98.2	115	12	53	24.3	12	47.9	20.1	-	-	-	-	-	-	-	-	-
COD	12	18.6	9.93	12	46.4	20.2	12	30	16.8	12	17	10.3	12	18.6	9.93	12	32.48	15.36046	12	34.78	15.6
TSS	12	14.3	3.55	12	18.3	7.7	12	12	2.62	12	11.8	4.34	12	14.3	3.55	12	16.3	5.137739	12	13.89	3.48
BOD	12	8.15	4.8	12	21.1	14.2	12	7.7	5.03	12	4.66	3.18	12	8.14	4.81	12	13.05	4.939175	12	9.8	5.83
Fe^{2+}	12	0.54	0.34	12	0.58	0.41	12	0.6	0.29	12	0.77	0.82	-	-	-	-	-	-	-	-	-
SO_4	12	32.1	9.33	12	33.5	7.18	12	35	5.9	12	34.9	5.96	-	-	-	-	-	-	-	-	-

Table S4 Average effluent concentration of water quality parameters contd.

	Season					
	Dry			Rainy		
	n	mean	SD	n	mean	SD
pH	35	7.08	0.195	49	7.12	0.18
DO	35	6.72	0.467	49	6.84	0.27
NO_3-N	35	6.1	2.564	49	6.52	3.2
NO_2-N	20	0.32	0.454	28	0.44	0.99
NH_4-N	35	3.32	2.333	49	1.83	1.61
PO_4	35	1.95	0.603	49	1.7	0.62
Cl^-	20	30.92	7.521	28	33.79	7.53
FCC	20	70.65	72.58	28	46.36	50.3
TCC	20	88.1	87.02	28	52.68	51.9
COD	35	27.01	16.65	49	29.23	17.8
TSS	35	15.04	6.343	49	13.87	3.64
BOD	35	12.68	10.24	49	8.72	6.38
Fe^{2+}	20	0.54	0.455	28	0.67	0.53
SO_4	35	32.45	7.594	49	34.93	6.67

Table S5 Removal efficiency of water quality parameters.

	Year																	
	2014			2015			2016			2017			2019			2020		
	n	mean	SD	n	mean	SD	n	mean	SD	n	mean	SD	n	mean	SD	n	mean	SD
pH	12	3.74	2.40	12	0.74	1.05	12	4.11	3.46	12	1.61	2.12	12	2.82	2.99	12	-0.06	2.85
DO	12	-104.3	63.72	12	-145.5	109.3	12	-66.85	43.8	12	-157.9	75.97	12	-187.0	170.1	12	-210.6	173.2
NO_3-N	12	-345.5	490.2	12	-326.1	316.6	12	-396.2	501.7	12	-139.8	157.8	12	-324.7	499.5	12	-123.6	148.0
NO_2-N	12	10.70	97.13	12	23.17	49.88	12	-7.36	121.1	12	-367.3	880.7	-	-	-	-	-	-
NH_4-N	12	-163.2	302.4	12	-73.86	189.0	12	58.23	41.41	12	-17.71	83.29	12	-12.13	94.21	12	-67.74	174.4
PO_4	12	22.49	21.97	12	-19.50	111.4	12	50.97	10.98	12	-4.86	51.14	12	19.79	27.53	12	18.91	29.99
Cl^-	12	15.30	15.71	12	8.34	15.54	12	13.09	8.68	12	18.09	14.62	-	-	-	-	-	-
SO_4	12	22.11	17.51	12	13.68	9.31	12	10.77	11.73	12	5.06	13.19	-	-	-	-	-	-
Fe^{2+}	12	46.80	60.92	12	58.66	20.16	12	57.05	14.90	12	26.66	72.66	-	-	-	-	-	-
BOD	12	92.31	5.22	12	84.13	7.97	12	91.80	8.16	12	96.93	1.64	12	92.32	5.22	12	89.49	4.75
TSS	12	92.87	1.86	12	89.66	4.89	12	90.55	4.06	12	94.21	2.88	12	92.88	1.86	12	91.74	1.75
COD	12	92.33	4.87	12	81.27	9.29	12	84.20	12.63	12	95.75	2.29	12	92.33	4.87	12	87.94	5.91
TCC	12	97.92	1.80	12	97.08	3.24	12	98.24	0.78	12	96.40	6.78	-	-	-	-	-	-
FCC	12	97.83	2.44	12	97.30	4.82	12	99.09	0.55	12	99.31	0.39	12	94.72	3.09	12	93.60	4.36

Table S5 Removal efficiency of water quality parameters contd.

Season								
2021			Dry			Rainy		
n	mean	SD	n	mean	SD	n	mean	SD
12	4.45	2.67	35	3.28	2.66	49	1.92	3.11
12	-103.9	79.60	35	-181.0	140.4	49	-109.8	90.2
12	-214.7	204.2	35	-202.1	225.0	49	-313.5	435.2
-	-	-	20	2.45	82.53	28	-147.8	599.7
12	50.40	34.82	35	-111.4	229.3	49	24.21	65.48
12	41.64	27.58	35	8.87	72.68	49	25.36	34.32
-	-	-	20	15.39	12.75	28	12.50	14.87
-	-	-	20	15.91	13.58	28	10.76	14.60
-	-	-	20	47.30	49.09	28	47.29	50.12
12	90.38	7.86	35	90.61	7.81	49	91.37	6.41
12	89.47	3.14	35	91.56	3.85	49	91.68	3.17
12	80.85	15.04	35	90.61	6.42	49	85.81	11.88
-	-	-	20	97.41	2.17	28	97.41	4.71
12	91.98	2.46	35	95.39	4.62	49	96.89	3.29

S2. GHG Emission and Energy Consumption

Table S6 Estimation of energy consumption characteristics of the WWTP

Treatment Stages	EC rate (kWh/m^3 of influent)*	% of total EC	EC rate (kWh/d)	GHG emission rate (kg CO_2 eq./d)
Preliminary stage				
Influent pumping	0.041	7.644	779	209.04
Coarse screening	0.000029	0.005	0.551	0.15
Fine screening	0.0042	0.783	79.8	21.41
Grit removal	0.0027	0.503	51.3	13.77
Secondary stage				
Mixer anoxic	0.16	29.827	3,040	815.75
Oxidation blowers	0.19	35.419	3,610	968.71
aerobic oxidation mixer	0.002	0.373	38	10.20
Final clarification	0.0084	1.566	159.6	42.83
Sludge recirculation	0.0079	1.473	150.1	40.28
Excess sludge pumping	0.0073	1.361	138.7	37.22
Tertiary stage				
UV lamps	0.11	20.506	2,090	560.83
Sludge treatment				
Gravity thickening	0.0019	0.354	36.1	9.69
Belt filter press	0.001	0.186	19	5.10
Total	0.536429	100	10,192.151	2,734.97

EC – Electricity Consumption; *- (Longo et al., 2016)

Table S7 Electricity consumption characteristics of the WWTP in seasons

		Electricity consumption	
Season	Inflow, Q (m^3/d)	TJ/d	kWh/d
Dry	12,000	0.02	6,437.15
Rainy	24,000	0.05	12,874.30

Table S8 Annual GHG emissions

	GHG emissions (kg CO_2 eq./year)				
Year	CO_2	CH_4	N_2O	GHG emissions (chemical use)	Total emissions
2014	1,958,635.19	4,136,622.96	158,307.39	10,592.48	6,264,158.03
2015	2,001,349.47	5,350,894.13	264,835.47	9,874.16	7,626,953.23
2016	1,914,481.11	4,516,670.60	315,279.11	7,242.60	6,753,673.42
2017	2,617,759.84	6,174,792.52	231,683.37	12,099.75	9,036,335.48
2019	1,958,635.19	4,454,861.27	176,269.23	10,594.40	6,600,360.09
2020	2,081,034.68	5,509,312.68	230,163.82	10,594.13	7,831,105.30
2021	1,869,048.21	4,541,374.91	365,070.43	7,195.08	6,782,688.63
Total	14,400,943.69	34,684,529.08	1,741,608.81	68,192.60	50,895,274.18
Average	2,057,277.67	4,954,932.73	248,801.26	9,741.80	7,270,753.45

Table S9 Seasonal GHG emissions

Site	Source	Season	GHG emissions (kg CO_2 eq./d)			
			CO_2	CH_4	N_2O	Total
On-site	Treatment line	Dry	1,995.859	1,0342.72	272.7895	12,611.36
		Rainy	3,112.347	1,5341.92	631.5143	19,085.78
Off-site	Discharge	Dry	155.4419	243.4135	128.1871	527.0424
		Rainy	352.47	350.6446	240.611	943.7256
	Electricity	Dry	1,717.174	6.488645	3.684624	1,727.347
		Rainy	3,434.347	12.97729	7.369247	3,454.694
	Chemical use	Dry	-	-	-	18.19029
		Rainy	-	-	-	32.76099

Table S10 GHG emission characteristics of the WWTP

Year	CO_2 (kg CO_2-eq.)	CH_4 (kg CO_2-eq.)	N_2O (kg CO_2-eq.)	Chemical use GHG emission (kg CO_2-eq.)	Total annual emission (kg CO_2-eq.)	Removed PU (kg/yr)	Electricity use (kWh/yr)	Total emissions (kg CO_2-eq./kg PU removed)	Electricity use (kWh/kg PU removed)	Influent (m^3/yr)	GHG emission (kg CO_2-eq./m^3)
2014	1,958,635	4,136,623	158,307.4	10,592.48	6,264,158	3,647,570	3,720,135	1.72	1.022	6,935,000	0.90
2015	2,001,349	5,350,894	264,835.5	9,874.163	7,626,953	3,541,095	3,720,135	2.15	1.052	6,935,000	1.10
2016	1,914,481	4,516,671	315,279.1	7,242.604	6,753,673	3,077,562	3,720,135	2.19	1.21	6,935,000	0.97
2017	2,617,760	6,174,793	231,683.4	12,099.75	9,036,335	5,359,672	3,720,135	1.69	0.69	6,935,000	1.30
2019	1,958,635	4,454,861	176,269.2	10,594.4	6,600,360	3,652,069	3,720,135	1.81	1.02	6,935,000	0.95
2020	2,081,035	5,509,313	230,163.8	10,594.13	7,831,105	3,923,677	3,720,135	2.00	0.95	6,935,000	1.13
2021	1,869,048	4,541,375	365,070.4	7,195.081	6,782,689	2,948,699	3,720,135	2.30	1.26	6,935,000	0.98
Average	2,057,278	4,954,933	248,801.3	9,741.8	7,270,753	3,735,763	3,720,135	1.98	1.03	6,935,000	1.05

S3. Sludge generation

Estimation of sludge generation (according to Andreoli et al. (2007))

(a) Since there is no primary clarifier/sedimentation at the WWTP, all sludge is assumed to be from secondary treatment. Therefore, sludge generated from influent to secondary treatment sludge to the gravity thickener is equivalent to $TSS_{in}\ load\ (kg\ TSS\ influent/d)$, the mass of influent TSS.

$$Sludge\ flow\ (m^3/d) = \frac{TSS_{in}\ load\ (kg\ TSS/d)}{\frac{Dry\ solids(\%)}{100} * sludge\ density\ (kg/m^3)}$$

Where, Dry solids = 0.6-1%, sludge density 1,001 kg/m^3.

(b) Thickened effluent sludge (sludge to be sent to the dewatering)

Thickened TSS effluent load, $TSS_{T\_eff}\ load\ (kg\ TSS/d)$ = Solids capture × Influent load

$$Influent\ load = TSS_{in}\ load - TSS_{out}\ load$$

$TSS_{out}\ load\ (kg\ TSS\ effluent/d)$ is the mass of effluent TSS. Solids capture for gravity thickening = 75-85%. The thickened sludge flow going to dewatering is estimated by:

$$Thickened\ Sludge\ flow\ (m^3/d) = \frac{TSS_{T\_eff}\ load\ (kg\ TSS/d)}{\frac{Dry\ solids(\%)}{100} * sludge\ density\ (kg/m^3)}$$

Dry solids = 2-7%, sludge density = 1,003-1,010 kg/m^3.

(c) Dewatered sludge production (sludge for final disposal)

Dewatered TSS effluent load, $TSS_{D\_eff}\ load\ (kg\ TSS/d)$ = Solids capture × Thickened TSS effluent load

Solids capture for dewatering by belt press = 90-95 %. The volume (flow) of dewatered sludge sent for final disposal is estimated by:

$$Dewatered\ Sludge\ flow\ (m^3/d) = \frac{TSS_{D\_eff}\ load\ (kg\ TSS/d)}{\frac{Dry\ solids(\%)}{100} * sludge\ density\ (kg/m^3)}$$

Dry solids = 20-40%, sludge density = 1,050-1,100 kg/m^3.

(d) Dry sludge (kg/d) = 0.3 * $TSS_{D\_eff}\ load\ (kg\ TSS/d)$.

Therefore, $S_{mass}(tonnes/yr) = \frac{dry\ sludge\ (kg/d)}{1{,}000} * 365$

Appendix D

Environmental and Economic Assessment of Electricity Recovery Technologies at a Wastewater Treatment Plant in Abuja, Nigeria.

S1. Sample Questionnaire from Wastewater treatment plant

Questionnaire for WWTP in Nigeria

1. Basic data

Position of respondent: SNR. CHEMICAL ENGINEER **Highest educational qualification:** M.SC

2. Location of WWTP

Address IDU INDUSTRIAL AREA, OPPOSITE NAPTIN, FCT, ABUJA.

City: ABUJA State: FCT Zip: Telephone number:

Email address:

When was the plant built? 2007

The functional life of the system 25-30 YEARS

The life span of pipes and tanks ....

3. Type of wastewater treated

Domestic ☐

Industrial ☐

Municipal ☑

Other ☐ ....

4. How many stages do your facility use? (Tick and List if known)

Stages		Chemical Consumption (type & qty)	Energy /Electricity Rating
Primary	☑	....	100 KVA *
Secondary	☑	....	200 KVA *
Tertiary	☑	....	200 KVA. *
Other	☑	....	100 KVA

5. Capacity of the treatment plant

Design Capacity 700,000 to 1,000,000 P.E.

Operation Capacity (Average flow) 1282.3 m^3/hr

Total population equivalent treated ....

Dry season flow 5500 m^3/hr

Rainy season /full flow to treatment 9000 m^3/hr.

Peak Daily Flow Estimate 9,000 m3/hr.

Energy consumption (per day or year): Diesel, Electricity, etc 3000 LITRES PER DAY

Operating assumptions (e.g., 10 h/day and 365 days/year) 365 DAYS/YEAR.

6. Treatment information (please attach system flow chart)

i. Primary treatment Processes

Processes	Size	Chemical Consumption (type & qty)	Energy /Electricity Rating
☑ Bar screens	CAPACITY: 4950m3/hr.		25 KVA
☑ Grit removal	4950m3		20 KVA
☐ Primary sedimentation			
☐ Comminution			
☐ Oil and fat removal			
☐ Flow equalization			
☐ pH neutralization			
☐			
☐			

ii. Secondary treatment Processes

Processes	Size	Chemical Consumption (type & qty)	Energy /Electricity Rating
☑ Activated Sludge	6 Units 27,700m3		45KVA
☐ Aerated lagoon			
☐ stabilisation pond			
☐ trickling filter			
☐ constructed wetlands			
☐ Extended aeration			
☐ Aquaculture			
☐			
☐			

Peak Daily Flow Estimate 9,000 m3/hr.

Energy consumption (per day or year): Diesel, Electricity, etc 3000 LITRES PER DAY

Operating assumptions (e.g., 10 h/day and 365 days/year) 365 DAYS/YEAR.

6. Treatment information (please attach system flow chart)

i. Primary treatment Processes

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☑ Bar screens	CAPACITY: 4950m³/hr.		25 KVA
☑ Grit removal	4950m³		20 KVA
☐ Primary sedimentation			
☐ Comminution			
☐ Oil and fat removal			
☐ Flow equalization			
☐ pH neutralization			
☐			
☐			

ii. Secondary treatment Processes

Processes	Size	Chemical Consumption (type & qty)	Energy /Electricity Rating
☑ Activated Sludge	6 units 27,700m³		45 KVA
☐ Aerated lagoon			
☐ stabilisation pond			
☐ trickling filter			
☐ constructed wetlands			
☐ Extended aeration			
☐ Aquaculture			
☐			
☐			

Peak Daily Flow Estimate 9,000 m3/hr.

Energy consumption (per day or year): Diesel, Electricity, etc 3000 LITRES PER DAY

Operating assumptions (e.g., 10 h/day and 365 days/year) 365 DAYS/YEAR.

6. Treatment information (please attach system flow chart)

i. Primary treatment Processes

Processes	Size	Chemical Consumption (type & qty)	Energy /Electricity Rating
☑ Bar screens	CAPACITY: 4950m3/hr.		25 KVA
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☐ Primary sedimentation			
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☐ Oil and fat removal			
☐ Flow equalization			
☐ pH neutralization			
☐			
☐			

ii. Secondary treatment Processes

Processes	Size	Chemical Consumption (type & qty)	Energy /Electricity Rating
☑ Activated Sludge	6 Units 27,700m3		45 KVA
☐ Aerated lagoon			
☐ stabilisation pond			
☐ trickling filter			
☐ constructed wetlands			
☐ Extended aeration			
☐ Aquaculture			
☐			
☐			

S2. Water Quality Parameters

ABUJA ENVIRONMENTAL PROTECTION BOARD
WUPA SEWAGE TREATMENT PLANT LABORATORY
RESULT OF LAB ANALYSIS

SAMPLE LOCATION: **WUPA STP**
DATE SAMPLED: **5TH SEPT.2022**
DATE ANALYSIS COMMENCES: **5TH SEPT.2022**
SAMPLES'OWNER; **Charles Ogbu**
PURPOSE OF ANALYSIS: **PhD Thesis**

Parameters	**Result**					
	Raw Sewage Before Treatment	**Primary Effluent (After Primary Treatment)**	**After Secondary Treatment**	**Final Effluent After UV Disinfection**	**Equipment Used**	**Method**
pH	7.09	7.50	7.23	7.44	pH 330i WTW	electrometric
Temperature *(^oC)*	27.8	27.8	27.2	27.0	pH 330i WTW	electrometric
Conductivity *(µʃ/cm)*	295	275	277	278	con 315 WTW	electrometric
Total Dissolved Solids (TDS) *mg/l*	131	146	122	121	(Oven) ED53 Binder	Gravimetric
Turbidity (NTU)	31.6	24.6	11.0	10.7	TURBIDITY METER (2100P)	NTU
Dissolved Oxygen *mg/l*	0.70	5.09	5.92	7.72	D.O METER OX4000H VWR	electrometric
Sulphate *mg/l*	45.0	43.0	40.0	40.0	Merck test kit	Turbidity
Biochemical Oxygen Demand (BOD) *mg/L*	120.0	110.0	7.0	7.0	BOD INDUCTIVE MEASURING SYSTEM (Oxitop WTW)	Respirometric
Total Suspended Solids (TSS) *mg/l*	100.8	80.6	13.6	10.0	(Oven) **ED53** Binder	Gravimetric
Chemical Oxygen Demand (COD) *mg/l*	216.3	214.4	13.2	13.0	THERMOREACTOR TR320(Merck kit)	Closed reflux
Ammonia as N *(mg/l)*	4.0	4.0	2.0	2.0	Merck test kit	photometric
Nitrate as N *(mg/l)*	2.8	2.5	3.0	2.5	Merck test kit	photometric
Nitrite as N *(mg/l)*	0.27	0.22	0.04	0.04	Merck test kit	photometric
Orthophosphate *(mg/l)*	2.80	2.20	0.7	0.7	Merck test kit	photometric
Total Nitrogen*(mg/l)*	21.0	16.0	15.0	14.0	THERMOREACTOR TR320 (Merck text kit)	photometric
Copper *(mg/l)*	2.00	1.90	0.80	0.80	,,	photometric
Zinc *(mg/l)*	0.18	0.07	0.03	0.03	,,	photometric
Iron*((mg/l)*	0.52	0.49	0.21	0.20	,,	photometric
Lead*(mg/l)*	0.46	0.34	0.12	0.09	,,	photometric
BACTERIOLOGICAL RESULT						
Total Coliform(CFU/100mL)	$9X10^5$	$7X10^5$	$14X10^4$	$2.2X10^2$	**Ocean Med, (Colony Counter Stuart)**	Pour plate
E. Coli (CFU/100mL)	$3X10^5$	$3X10^5$	$10X10^3$	$2X10^2$	**Ocean Med, (Colony Counter Stuart)**	Pour plate

Appendix E - List of publications

Accepted/Published

Ogbu, C.A., Alexiou Ivanova, T., Ewemoje, T. A., Okolie, C. O., & Roubik, H. (2023). Techno-economic analysis of electricity generation from household sewage sludge in different regions of Nigeria. Science of The Total Environment, 166554. https://doi.org/10.1016/j.scitotenv.2023.166554

Roubík, H., Lošťák, M., Ketuama, C. T., Soukupová, J., Procházka, P., Hruška, A., ... Ogbu, C.A., & Hejcman, M. (2023). COVID-19 crisis interlinkage with past pandemics and their effects on food security. Globalisation and Health, 19(1), 52. https://doi.org/10.1186/s12992-023-00952-7

Ogbu, C.A., Ivanova, T.A., Ewemoje, T.A., Hlavsa, T. and Roubik, H. (2023), Estimating the Ecological Performance of Water and Wastewater Treatment in Africa: A Meta-Analysis. Chem. Eng. Technol., 46: 1078-1088. https://doi.org/10.1002/ceat.202200562

Ogbu, C.A., Jelínek, M., Alexiou-Ivanova, T., & Corman, I. (2022). The More Wine, the More Gas? Estimation of the Bioenergy Potential of Winery Wastewater in Moldova. https://doi.org/10.55505/sa.2022.1.12

Submitted/In Process

Ogbu, C.A., Alexiou Ivanova, T., Ewemoje, T.A., Alabi, H.A., Roubík, H. (Under review at International Journal of Life Cycle Assessment). Comprehensive Review of Life Cycle Assessment Studies of Water and Wastewater Treatment in Africa.

Ogbu, C.A., Alexiou Ivanova, T., Ewemoje, T.A., Oluwadamisi, E., Roubík, H. (Submitted to Environmental Science: Water Research & Technology) Evaluation of Performance and Carbon Footprint of a Wastewater Treatment Plant in Abuja, Nigeria.

Ogbu, C.A., Alexiou Ivanova, T., Ewemoje, T.A., Ajekiigbe, D.A., Salawu, M.E., Oluwadamisi, E.A., Roubík, H. (to be submitted to Energy for Sustainable Development) Environmental and Economic Assessment of Electricity Recovery Technologies at a Wastewater Treatment Plant in Abuja, Nigeria.

Appendix F - Conferences

Presentations

Ogbu C. A, T. Ivanova, H. Roubík. (August 2022). Poster: Estimation of the ecological performance of water treatment: A meta-analysis of energy use and environmental impacts in Africa. 26th International Congress of Chemical and Process Engineering CHISA 2022

Ogbu C. A, T. Ivanova, C. M. J. Pausta, D. P. Saroj, H. Roubík. (August 2022). Oral presentation: Influence of effluent discharge standard and source of electricity on environmental loading: LCA of a sewage treatment plant in Nigeria. CHISA 2022

Ogbu C. A, Jelínek, M., Alexiou-Ivanova, T. (October 2022). Oral Presentation: More Wine More Gas? Estimation of the Bioenergy Potential of Winery Wastewater in Moldova: Contribution to Sustainable Development. International Scientific and Practical Symposium. The use regulation of natural resources: achievements and perspectives.

Ogbu, C.A., Alexiou Ivanova, T., Roubík, H. (September 2022). Poster: Food for all, water for all, agriculture takes it all: Water management in African agriculture. Tropentag 2022, Germany.

Ogbu, C.A., Ewemoje, T.A., Alexiou Ivanova, T. (October 2021). Poster: Life Cycle Assessment of Wastewater Treatment- the position of the African Continent. Nature Conference: Waste Management and Valorisation for a Sustainable Future.

Ogbu, C.A., (November 2021). Online Presentation: Life Cycle Management- Environmental & Economic considerations. AgriSciences Platform for the enhancement of HEIs in Ukraine (APSEHU).

Attendance

International Water Association Digital World conference 2021. May 24 – 4 June 2021.

Synergies between zero-pollution & resource recovery targets in Urban water cycle. 28.05.2021. Online Seminar. EU Green week 2021 partner event.

Appendix G - Author's CV

Charles Amarachi Ogbu, M.Sc.

ogbucharlesamarachi@yahoo.com | **LinkedIn** | **ResearchGate** | Prague | (+420) 603479831

EDUCATION

PhD, Sustainable Technologies, Czech University of Life Sciences Prague. 10/2024
Thesis: Environmental Assessment of Wastewater Treatment-based Resource Recovery in Nigeria.

Master of Science, Environmental Engineering, University of Ibadan, Nigeria. 2017
Thesis: Potentials of increasing levels of recycled waste plastic on the physical characteristics of concrete.

Bachelor of Eng., Soil & Water Engineering, Federal University of Technology Owerri, Nigeria. 2013
Thesis: Fabrication of hand water pump for irrigation.

EXPERIENCE

Faculty of Tropical AgriSciences, CZU Prague, 10/2020 – date
Research and Teaching Assistant

- Assessed environmental impact and carbon footprint of systems using life cycle assessment tools such as MS Excel, Origin, SimaPro, and other methodologies (e.g., IPCC, PEF EN 15804).
- Comparative techno-economic analysis of energy recovery alternatives.
- Performed waste audit for implementation of waste-to-energy technologies.
- Systematically reviewing sustainability studies using meta-analytic methods using R Software.
- Familiarisation with environmental standards: ISO 14001:2015, 14040:2006, and 14044:2006.
- Mentoring and advising theses students on content, structure, use of English, and presentation.
- Teaching, presenting at conferences, and publishing high-impact journal articles.

Industrial Process Systems Eng. Unit, NTU Athens 02/2023 – 04/2023
Ontology Research Intern

- Conducted research and contributed to the development of ontology-based knowledge representation systems. Supervised by: Dr. Nikos Trokanas, and Prof. Antonio Kokossis.

- Designed and implemented data models for a semantic web application.
- Utilized Protégé and OWL to create and maintain ontologies.

Dept. of Agric. & Environmental Eng., Univ. of Ibadan, Nigeria 01/2017 – 06/2017
Graduate Researcher

- Designed experiments for mixing, casting, and testing of concrete specimens.
- Determined the particle sizes of different aggregates (fine, coarse, and waste plastic).
- Formulated moulds, performed slump tests, and curing of concrete specimens.
- Conducted compressive, splitting tensile, and flexural strength tests on concrete specimens.

OTHER WORK EXPERIENCE

Vertex Professional Services, Prague, **Training Administrator** 02/2022 – 11/2023

- Analysed Learning Mgt. Systems (LMS) (e.g., Cornerstone, Totara) activity logs maintaining support for 500+ objects and 800k+ users from 50+ countries.
- Tracked request logs on Service Now/Jira, resulting in an 85% L1 ticket resolution in 16 hours.
- Managed learning resource data to optimise content delivery, resulting in a 15% increase in module utilisation.
- Generated reports on training effectiveness metrics, leading to a 30% increase in user satisfaction. Tools & platforms: Cornerstone, Totara, DriveIT, Adobe Connect, MS Excel, Microsoft Office 365.

Czech University of Life Sciences, Prague, **Project Support** 11/2020 – 08/2021

- Actively participated in reporting, communication and correspondence between project partners.
- Contributed to literature reviews and feasibility studies before project application.
- Liaised with local partners to arrange logistics and project implementation itinerary.
- Installed briquetting presses and biogas plants in wineries to convert waste to energy.
- Participated in the data collection on production value chain and waste management. e.g., turning winery waste into profit: Czech-UNDP partnership for SDGs cooperation project.

Holy Family Industries Nig. Ltd., Owerri, Nigeria, **Production/Quality control officer** 01/2018 – 10/2020

- Monitored water production and tested water samples to evaluate quality and safety.
- Adjusted pH levels, filters, pumps, and other equipment to maintain best water quality.
- Disinfected water with chemicals such as ammonia and chlorine in exact concentrations.
- Monitored water quality and adjusted chemical dosage to meet regulatory standards.
- Regular calibration of analytical instruments to meet industry standards.
- Recommended strategies for waste reduction and optimisation of water and energy use.

Akwa Ibom Rural Water and Sanitation Agency, Uyo, Nigeria, **Engineering Trainee** 08/2014 – 08/2015

- Analysed water usage to identify usage hotspots of UNICEF WASH Projects.
- Performed energy and water audits with the Engineering unit.
- Inspected completed projects and approved standards before client delivery, such as UNICEF WASH Projects in Nsit Atai L. G. A. Akwa Ibom State.
- Improved process efficiency of projects through reduction of energy use and water consumption.
- Part of the project team tasked with reviewing, negotiating, and approving bills of Quantities.

Teaching and Mentorship Activities

Teaching Involvements

- Management of Energy Resources: Summer Semester 2021, 2022, 2023, 2024
- Environmental Engineering: Summer Semester 2021, 2022, 2023, 2024
- Appropriate Rural Technologies: Summer Semester 2021, 2022, 2024

Thesis Consultation/Award Date (Principal Supervisor: Assoc. Prof. T. A. Ivanova)

- Chinedu Osita Okolie. Assessment of Electricity Production from Anaerobic Digestion and Incineration of Household Sewage Sludge in Nigeria (MSc. Thesis; Ongoing).
- Nariputhisak Vong. Assessment of the environmental and economic potential of biomass in Cambodia (Bachelor Thesis; 20 April 2023).

- Anton Handal. Energy situation in Palestine - the prospect of agricultural residual biomass in energy marginalised areas (Bachelor Thesis; 6 August 2021).

RESEARCH AND DEVELOPMENT PROJECTS

Modernization and raising the prestige of Higher Agricultural Education in Moldova, Republic of Moldova. 2024
Donor: Ministry of Foreign Affairs of the Czech Republic. Position: **Project expert**.

Appropriate technologies in waste and water management [grant number 20223108]. 2023
Donor: Internal Grant Agency of the Faculty of Tropical AgriSciences, CZU Prague. Position: **Ph.D. researcher.**

Strengthening scientific capacities and cooperation of Ukrainian universities in AgriSciences: Platform for the enhancement of HEIs in Ukraine (APSEHU), Ukraine. 2022 – 2023
Donor: Ministry of Foreign Affairs of the Czech Republic. Position: **Project expert**.

Appropriate technologies in waste and water management [grant number 20223110]. 2022
Donor: Internal Grant Agency of the Faculty of Tropical AgriSciences, CZU Prague. Position: **Ph.D. researcher**.

Support of teaching innovation, Research development and Inter-university cooperation of SAUM and TSU (Moldova), Republic of Moldova. 2021 – 2022
Donor: Ministry of Foreign Affairs of the Czech Republic. Position: **Project expert**.

Research on environmental and sustainable technologies for developing countries [grant number 20213108]. 2021
Donor: Internal Grant Agency of the Faculty of Tropical AgriSciences, CZU Prague. Position: **Ph.D. researcher**.

Turning wine waste into profit: possibilities of the Moldavian wine industry, Moldova. 2020 – 2021
Donor: United Nations Development Programme (UNDP). Position: **Technical support**

NETWORKS AND MEMBERSHIPS (membership no./year joined)

International Association of Engineers (IAENG) |353958 | 2023

International Water Association (IWA) |1623805| 2021

American Society of Agricultural and Biological Engineers (ASABE) |1055558| 2018

Pan African Society for Agricultural Engineering (PANSAE) |IM025| 2018

HONOURS AND AWARDS

Doctoral Scholarship - Czech University of Life Sciences, Prague	2020 - 2024
Erasmus+ Internship for Training	2023
Student Mobility Scholarship, Czech University of Life Sciences, Prague	2022
e-Competition Writers' Award YPARD/AGRINATURA	2021

SKILLS

Knowledge: Sustainability Assessment & Reporting, Waste-to-energy, Global Warming, GHG Emissions.

Digital Skills: Microsoft Office Suite, R Software, Origin, SimaPro, Cornerstone, Totara, Jira, ServiceNow.

Soft Skills: Time & Team Management, Communication, Problem Solving, Critical Thinking, Attention to Detail.

LANGUAGES

English (native level) |Igbo (native level)| Hausa (conversational level)

TRAINING AND CERTIFICATIONS

Meta-science Summer School - Friedrichsdorf 09/2023
Berlin Institute of Health (BIH), Germany

Open Science Summer School 09/2023
University of Maribor, Slovenia

Data Science Foundations: Knowledge Graphs 02/2023
LinkedIn Learning

Academic writing, Working with Information and databases 02/2021
University Grant Commission, Czech University of Life Sciences Prague

Statistical Data Analysis Training 12/2020
Czech Republic Development Cooperation

English Language Proficiency Certificate (Score: 102/120) 11/2019
TOEFL iBT, Education Testing Service

Awareness on Environmental Management – ISO 14001 05/2019
Standards Organization of Nigeria

Project Management Professional (PRINCE2) Certification 06/ 2015

Novelle Center, Uyo, Akwa Ibom State. Nigeria
Environmental Awareness Certifications 05/2015
British International Safety Organization

VOLUNTEER EXPEREINCE

My World Survey Volunteer, United Nations. 04/2015 – 08/2015
Collected data on public priorities for sustainable development in Uyo, Nigeria.

Reporter, U-report Nigeria. 11/2014 – 12/2015
Provided community-level information on social issues, enhancing engagement and advocacy.

Provost, Millennium Development Goals Group. 02/2015 – 12/2015
Organized community sensitization activities on sanitation, hygiene, and primary education.