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Estimating the Ecological Performance of Water and Wastewater Treatment in Africa: A Meta-Analysis

This article is the result of a systematic review of published life cycle assessment (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 method. There is a need for more such LCA studies in Central and Western parts of Africa.

Supporting Information available online

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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 involve the LCA approach, the impact assessment methodology, the impact indicators, and the uncertainty analysis. However, typological concerns comprise 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].

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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 employed 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.

2 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 the 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 involved in this report 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 (Fig. 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 given in Supporting Information (Sect. S1).

3 Results and Discussion

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

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. Fig. 2 presents 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 % considered raw water and industri-

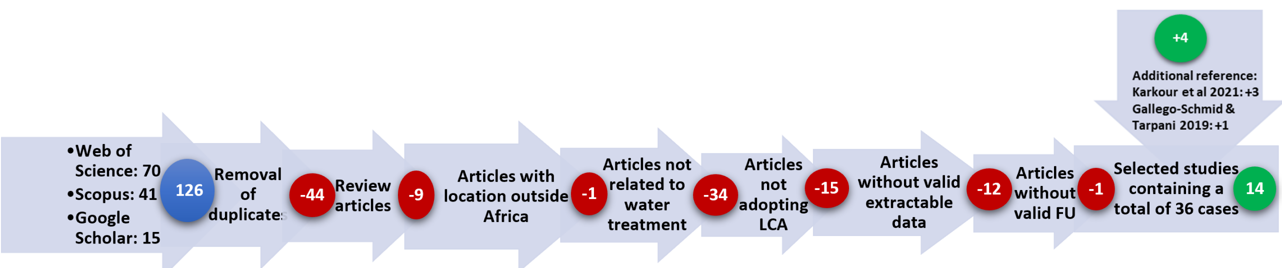

Figure 1. Process of article screening for establishing the relevant LCA studies for water treatment.

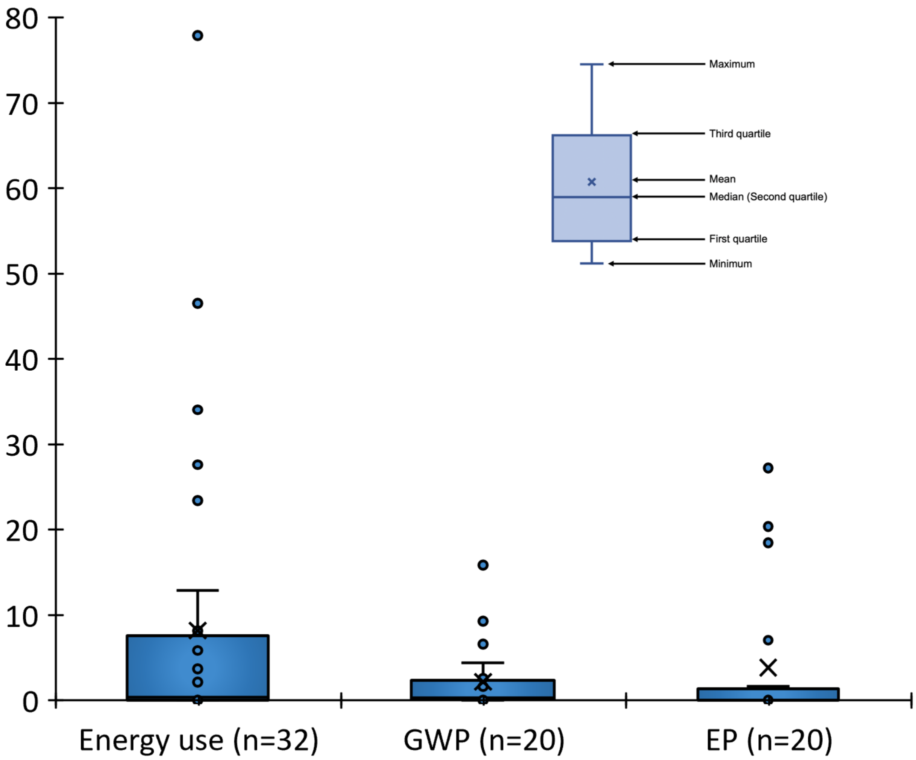

Figure 2. Summary statistics of energy use and impact categories for water treatment studies. Energy expressed in kWh m^{-3}, GWP in kg CO_2-eq m^{-3}, EP in 10^{-2} kg PO_4^{3-}-eq m^{-3}, n = number of observations.

al WW treatment each. Most of the studies reflected 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 life cycle impact assessment (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.

Moreover, the cumulative number of studies (CNS) published rose abruptly from 2009, as indicated in Fig. 3. This trend aligns with those of LCAs 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 (TWs), 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.

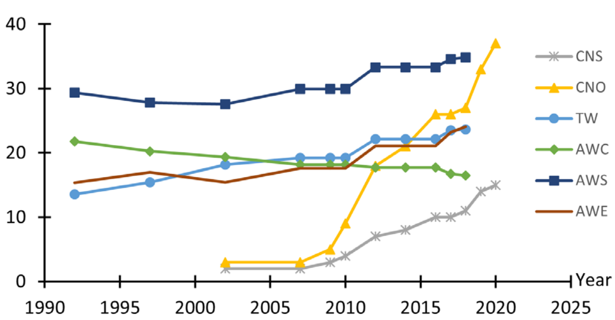

Figure 3. Cumulative number of studies and observations per publication year; and FAO water metrics. CNS, cumulative nos. of studies; CNO, cumulative nos. of observations; TW, total withdrawal (10^{10} $m^{-3}a^{-1}$); AWC, average withdrawal per average withdrawal per capita (×10 $m^{-3}a^{-1}$ per inhabitant); AWS, average water stress (%); AWE, average water use efficiency (USD m^{-3}).

3.2 Description of Results

Statistical analysis of 36 case studies indicates that for EIs, the GWP vary from 1.69×10^{-14} to 15.9 kg CO_2-eq m^{-3}, and EP range from 1.3×10^{-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 depicted in Fig. 4. The general analysis showed that the energy consumption and environmental impacts var-

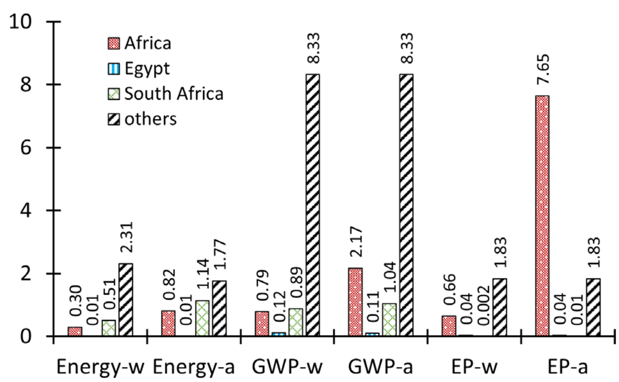

Figure 4. Summary estimates for energy use and EIs of observations by geographical location expressed as pooled (–w) and arithmetic (–a) means. Energy (×10^1 kWh m^{-3}), GWP (kg CO_2-eq m^{-3}), EP (×10^{-1} kg PO_4^{3-}-eq m^{-3}). Others = Africa less Egypt and South Africa.

ied significantly owing to certain factors. Complete statistical description of energy use, GWP, and EP with the associated variable families is presented in the Supporting Information (Tab. S2). The detailed calculation of the pooled mean by location and water source is given in the Supporting Information (Figs. S1–S12). Subsequently, a detailed analysis of the influence of these significant factors was demonstrated.

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 geomorphological 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 and 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 $2.414\times10^9\,m^3a^{-1}$ (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 like natural and aerated lagoons in Morocco [34], rapid sand filtration [35], and filtration, wetlands [36], and activated sludge [37] in Egypt were also utilized.

Moreover, energy-intensive technologies for water treatment have 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, and gas. 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 strongest 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, biochemical oxygen demand (BOD), and chemical oxygen demand (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 $kg\,CO_2$-eq 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, total Kjeldahl nitrogen (TKN), NH_4, NO_3, NO_2, PO_4^{3-}, total suspended solids (TSS), and total phosphorus (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 ($\times 10^9\,m^3$) 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].

Fig. 5 displays the proportions of treated, untreated, and direct use of untreated municipal WW for irrigation purposes in Africa compared to other countries. 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 ($mg\,O_2\,L^{-1}$) limit of 30–50, Tanzania 30, and 50 for Ghana, Uganda, and Malaysia, respectively. For DS ($mg\,L^{-1}$), Thailand and Tanzania had as high as 3000 and low as 200 in Nigeria. Other parameters, such as COD and soluble solid (SS), showed wide discrepancies [51]. These inconsistencies in parameters reflect in the discharges and, consequently, EP values.

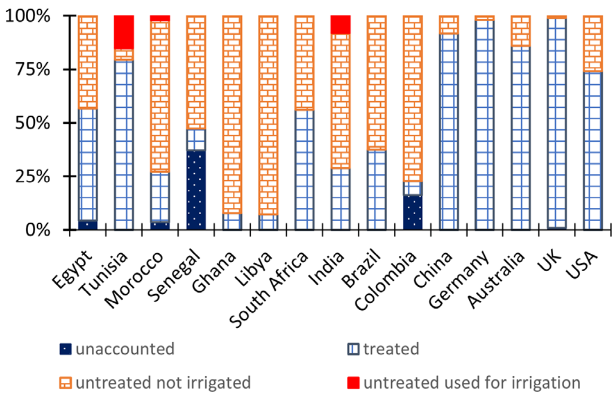

Figure 5. Characteristics of municipal wastewater in several countries. Unaccounted equals produced wastewater less the treated and untreated fractions.

3.2.2 Water Source

The mean values of energy use and EIs in the treatment of raw water and wastewater are displayed in Fig. 6. As mentioned earlier, only 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 loca-

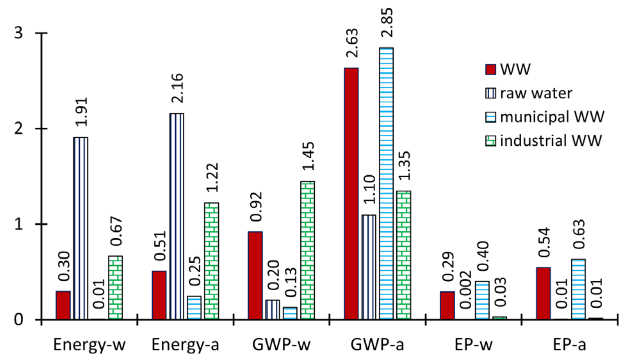

Figure 6. Summary estimates for energy use and EIs of observations by the source of treated water as pooled (–w) and arithmetic (–a) means. Energy ($\times 10^1$ kWh m^{-3}), GWP (kg CO_2-eq m^{-3}), EP ($\times 10^{-1}$ kg PO_4^{3-}-eq m^{-3}).

tions, 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 EI intensities [6].

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 and 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 0.38–1.22 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) processes, 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, a 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 requires 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. 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].

3.2.3 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 presented in Tab. 1, together with the results obtained for energy use, GWP, and EP. 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 Tab. 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 $\leq$ 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 Fig. 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 that treatment processes in

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

Model	Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
	Energy [kWh m^{-3}]		GWP [kg CO_2-eq m^{-3}]		EP [kg PO_4^{3-}–eq m^{-3}]	
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***	2.12×10^{-12}	0.001***	4.26×10^{-14}
Raw water	1.53***	7.6×10^{-13}				
Geographical 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***	6.05×10^{-6}
O			–5.206***	0.052	–0.006***	1.06×10^{-5}
LCIA method						
CML (ref)						
Eco-indicator						
ReCiPe						
Others						
Software						
GaBi (ref)						
SimaPro			5.938***	2.6×10^{-12}	0.006***	8.14×10^{-12}
Others			5.037***	0.072		
Study typology						
Year of publication			–0.202***	2.91×10^{-11}	-2.12×10^{-4} ***	5.31×10^{-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. This is a standard convention for representing significant levels irrespective of the levels that appears in our results. The asterisks represent the levels. The empty cells represent insignificant outcomes.

South Africa consume about 75.77 $kWh\,m^{-3}$ less than in Egypt. But the visual from descriptive statistics in Fig. 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. 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 EI results. Most of these discrepancies were attributed to energy/electricity mix, electricity rates, demography, economic and industry outlook, and the geomorphology 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 exhibited 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 modeling 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, the publication year has a significantly negative (p-value < 0.01) impact 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 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 applied 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:

- 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.
- Furthermore, GWP suggests a substantial correlation with the intensity of energy use, as reported 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.
- Additionally, EP estimates are higher for municipal wastewater treatment than for 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, modeling 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.

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.

Future research can analyze estimates for each of the three predominant stages of the life cycle. 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].

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Abbreviations

AAO	anaerobic/anoxic/oxic
AO	anoxic/oxic
AWC	average withdrawal per capita
AWE	average water use efficiency
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 gas
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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