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Trade-offs among energy use, effluent quality, and temporal variability in full-scale municipal wastewater treatment: A three-year comparative benchmark

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ABSTRACT

Selecting a municipal wastewater-treatment technology requires more than comparing removal percentages because similar effluent quality can be achieved at substantially different energy and operational costs. This study developed a decision-oriented benchmark for three full-scale biological configurations – activated sludge, trickling filter, and natural lagooning – using 108 monthly plant records collected from January 2022 to December 2024 in north-central Morocco. Influent and effluent five-day biochemical oxygen demand, chemical oxygen demand, and total suspended solids were combined with treated volume and electricity use to calculate concentration-based and load-weighted removal, specific energy consumption, and electricity use per kilogram of five-day biochemical oxygen demand removed, while temporal variability was characterized from monthly and semester-level records. Activated sludge delivered the highest overall load-weighted removals (93.4%, 93.5%, and 93.9%, respectively) but required 0.651 kWh/m³. The trickling filter achieved 89.2%, 88.6%, and 92.4% removal at 0.319 kWh/m³ and 0.990 kWh per kilogram of five-day biochemical oxygen demand removed. Natural lagooning used only 0.018 kWh/m³ and removed 92.4% of five-day biochemical oxygen demand, but total suspended solids removal was lower and more variable (67.3%). Monthly specific energy consumption differed among configurations (Kruskal–Wallis $H = 90.39$, $p < 0.001$), and all Holm-adjusted pairwise comparisons were significant ($p < 0.001$). A qualitative Pareto interpretation identified activated sludge as the quality-priority option, natural lagooning as the electricity-minimization option, and the trickling filter as the most balanced solution under the studied conditions. The benchmark converts routine operational data into a transferable technology-selection framework for small and medium-sized communities in water-scarce and energy-constrained regions.

Keywords: energy efficiency, full-scale wastewater treatment, Pareto interpretation, semi-arid regions, technology selection, temporal variability.

INTRODUCTION

Municipal wastewater treatment is increasingly evaluated as a resource-efficiency problem rather than solely as a pollution-control operation. Treatment plants must protect receiving waters while limiting electricity demand, operating expenditure, and indirect greenhouse-gas emissions. Processes that provide tight control of aeration, solids retention, and sludge recirculation commonly require more energy than passive or attached-growth systems (Longo et al., 2016; Maktabifard et al., 2018). Energy self-sufficiency studies likewise identify process configuration as a central constraint (Gu et al., 2017). Full-scale surveys show that plant size and influent strength strongly influence specific electricity consumption (Mizuta and Shimada, 2010; He et al., 2019). Discharge requirements and local operating conditions further affect observed energy intensity (Panepinto et al., 2016). Consequently, ranking technologies using removal efficiency alone can lead to incomplete or misleading engineering decisions.

Activated sludge can achieve stable organic-matter and suspended-solids removal, but its dependence on mechanical aeration is a major energy burden (Metcalf and Eddy/AECOM, 2014; Nowak et al., 2015). Trickling filters use attached biofilms and natural or forced ventilation, potentially lowering electricity demand while maintaining robust treatment. Natural lagooning relies mainly on long hydraulic retention, sedimentation, sunlight, and biological interactions (Mara, 2013; Spellman, 2013). Pond performance can nevertheless be affected by seasonal conditions, algal solids, hydraulic short-circuiting, and resuspension (Ho et al., 2017; Lian et al., 2022). Comparative technology surveys also emphasize that process selection must reflect local climatic, economic, and institutional conditions (Noyola et al., 2012). These contrasting mechanisms make the three configurations particularly suitable for investigating quality–energy–variability trade-offs.

Most plant assessments report either effluent quality or energy intensity, whereas fewer studies integrate load-weighted pollutant removal, electricity per unit pollutant removed, and temporal variability using comparable full-scale records. Existing benchmarking studies demonstrate the value of plant-specific operational data (Abusam et al., 2004; Longo et al., 2016). Later work emphasizes function-based indicators and cautions that a single universal energy indicator can conceal differences in scale, loading, and treatment objectives (Longo et al., 2019; Gallo et al., 2024). Broader water-cycle studies show that energy demand must be interpreted together with pollutant removal and environmental burdens (Plappally and Lienhard, 2012; Venkatesh and Brattebø, 2011). Life-cycle assessment likewise demonstrates that operational electricity is only one component of environmental performance (Corominas et al., 2013). This gap is especially important for small and medium-sized communities in semi-arid regions, where land availability, electricity reliability, water scarcity, and operator capacity jointly shape technology choice. The objective of this study was therefore to develop and apply a decision-oriented benchmark for three anonymized full-scale wastewater-treatment configurations in north-central Morocco. The scientific novelty lies in combining routine monthly monitoring data with load-based indicators, temporal variability, and a qualitative Pareto interpretation to identify process-specific decision zones rather than declaring a single universally superior technology.

MATERIALS AND METHODS

Study sites and operational dataset

The study was conducted at three full-scale wastewater treatment plants treating predominantly urban domestic wastewater. To preserve operational confidentiality, the sites are identified by their treatment configurations: activated sludge wastewater treatment plant (AS-WWTP), trickling filter wastewater treatment plant (TF-WWTP), and natural lagooning wastewater treatment plant (NL-WWTP). The approximate design populations are 15,500 population equivalents for AS-WWTP, 57,600 population equivalents for TF-WWTP, and 28,600 population equivalents for NL-WWTP. Monthly aggregated records were available from January 2022 to December 2024, corresponding to 108 station-month observations. Study-site characteristics and calculated annual influent volumes are summarized in Table 1.

Table 1. Available study-site characteristics and calculated annual influent treated volumes

Station	Treatment process	Design population (PE)	2022 volume (m³)	2023 volume (m³)	2024 volume (m³)
AS-WWTP	Activated sludge	15,500	932,865	1,018,504	886,320
TF-WWTP	Trickling filter	57,600	1,736,346	1,674,416	1,807,560
NL-WWTP	Natural lagooning	28,600	500,424	501,642	832,424

Note: PE: population equivalent. Volumes were calculated from monthly mean influent flow multiplied by the number of calendar days in the corresponding month.

The plants differed in design population and treatment mechanism, allowing comparison across realistic operating scales. Exact geographic coordinates and detailed layouts were withheld to preserve operational confidentiality. The analysis therefore focuses on reproducible process indicators rather than site identification.

Monitoring parameters and data aggregation

Treatment performance was evaluated using influent and effluent concentrations of five-day biochemical oxygen demand (BOD_5), chemical oxygen demand (COD), and total suspended solids (TSS). Electricity-consumption data were obtained from the plant operating records. The analysis considered reported total electricity use associated with treatment operations, including pumping, aeration where applicable, sludge recirculation, and auxiliary equipment. The source spreadsheets provide monthly aggregated concentrations, mean flow rates, and monthly electricity use. Semester-level values shown in Figures 1–3 are arithmetic means of the six corresponding monthly records.

The analysis used routine monitoring records supplied by the plant operators. The same core variables – monthly mean influent and effluent flow, electricity consumption, and influent and effluent concentrations of five-day biochemical oxygen demand, chemical oxygen demand, and total suspended solids – were available for all three configurations. Because the records were generated under full-scale operating conditions rather than a controlled experiment, differences in influent strength, hydraulic loading, and local operation were treated as part of observed system performance. Detailed sampling protocols and laboratory worksheet-level quality-assurance records were not available in the anonymized operational database; this limitation was considered in the interpretation.

To ensure inter-plant comparability, the three facilities were monitored within the same institutional sampling and laboratory framework. Wastewater sampling followed harmonized procedures based on the ISO 5667 series, including ISO 5667-10 for wastewater sampling. BOD_5 was determined using an OxiTop respirometric method, COD using a colorimetric method based on ISO 15705:2002, and TSS using a gravimetric method based on NM EN 872:2013. The same parameter definitions, reporting units, and quality-control principles were applied to all three facilities; therefore, the comparative analysis was based on results generated under a common analytical framework.

The anonymized summary indicators, descriptive statistics, quality-control notes, corrected TF-WWTP monthly record set, and recalculated NL-WWTP summary indicators are provided in the Supplementary file.

Calculations

Concentration-based removal efficiency was calculated using Equation 1:

$$\eta = ((C_{in} - C_{out}) / C_{in}) \times 100 \tag{1}$$

where: η is removal efficiency (%), C_{in} is influent concentration (mg/L), and C_{out} is effluent concentration (mg/L).

Monthly treated volume was calculated using Equation 2:

$$V_m = Q_{in,m} \times d_m \tag{2}$$

where: V_m is monthly treated volume (m^3), $Q_{in,m}$ is monthly mean influent flow (m^3/d), and d_m is the number of calendar days in month m.

Specific energy consumption was calculated using Equation 3:

$$SEC = E / V \tag{3}$$

where: SEC is specific energy consumption (kWh/m^3), E_m is monthly electricity use (kWh), and $V_{in,m}$ is monthly influent treated volume (m^3).

Monthly influent and effluent pollutant loads were calculated using Equations 4 and 5:

$$L_{p,in,m} = C_{p,in,m} \times V_{in,m} \times 10^{-3} \tag{4}$$

$$L_{p,out,m} = C_{p,out,m} \times V_{out,m} \times 10^{-3} \tag{5}$$

where: $L_{p,in,m}$ and $L_{p,out,m}$ are monthly influent and effluent loads of pollutant p (kg/month), $C_{p,in,m}$ and $C_{p,out,m}$ are concentrations (mg/L), and $V_{in,m}$ and $V_{out,m}$ are monthly influent and effluent volumes (m^3).

Overall load-weighted removal was calculated using Equation 6:

$$\eta_p, load = [\Sigma_m(L_{p,in,m} - L_{p,out,m}) / / \Sigma_m L_{p,in,m}] \times 100 \tag{6}$$

Electricity use per kilogram of five-day biochemical oxygen demand removed was calculated using Equation 7:

$$EI^{BOD_5} = \Sigma_m E_m / \\ / \Sigma_m (L^{BOD}{}_{5,in,m} - L^{BOD}{}_{5,out,m}) \quad (7)$$

where: EI^{BOD_5} is electricity use per kilogram of five-day biochemical oxygen demand removed (kWh/kg).

Annual concentration-based efficiencies were calculated from annual mean concentrations, whereas overall load-weighted indicators used summed monthly loads over 2022–2024.

Statistical analysis

Monthly specific energy consumption values were summarized using the mean, standard deviation, median, and interquartile range. Normality was assessed using Shapiro–Wilk tests and homogeneity of variance using a median-centered Levene test. Because the distributions departed from normality and variances differed, a non-parametric Kruskal–Wallis test was used to compare the three configurations. Pairwise Mann–Whitney tests with Holm correction were applied for post hoc comparisons. Statistical significance was assessed at $p < 0.05$. The comparison is exploratory because the monthly values represent repeated operational measurements and temporal autocorrelation was not modeled.

To quantify temporal stability, the arithmetic mean, sample standard deviation, and coefficient of variation (CV = 100 × SD/mean) were additionally calculated from the 36 monthly observations for effluent BOD_5, COD, TSS, and specific energy consumption. Differences in dispersion among the three configurations were assessed using median-centered Levene (Brown–Forsythe) tests, with Holm-adjusted pairwise comparisons when the overall test was significant. Because CV is a relative measure and may be inflated when the mean concentration is low, CV values were interpreted together with absolute effluent concentrations and the dispersion tests.

Decision-oriented comparison

A qualitative non-dominance interpretation was applied to overall load-weighted removal, specific energy consumption, electricity use per kilogram of five-day biochemical oxygen demand removed, and observed temporal variability. A configuration was considered non-dominated when no alternative improved one major criterion without worsening at least one other criterion. Because only three configurations were compared and no composite objective function was fitted, this step was descriptive rather than a formal multi-objective optimization.

Data-quality screening

The spreadsheets were screened for transcription anomalies and abrupt changes. Records directly used for the core pollutant, flow, and energy calculations were retained unless a correction could be made unambiguously. The operator-provided corrected NL-WWTP workbook replaced the previously flagged October-November 2023 pollutant values. The operator-provided corrected TF-WWTP workbook was used to replace the previously flagged flow records, including the October 2024 value. The corresponding indicators were recalculated. Remaining quality-control observations are documented in Dataset_1.xlsx.

Quality control was restricted to variables used in the core calculations. Corrected operator records were retained for the trickling-filter flow series, including the October 2024 value, and previously corrected natural-lagooning records were preserved. Ancillary variables that could not be consistently verified across all plants were excluded from comparative inference.

RESULTS

Temporal trends in water-quality parameters and electricity use

Semester-level trends are presented in Figures 1–3. Each point represents the arithmetic mean of six monthly records and is used to describe temporal patterns; overall process comparison is based on load-weighted and energy-normalized indicators.

At AS-WWTP, influent BOD_5 varied from approximately 210 to 318 mg O_2/L at the semester scale, whereas effluent BOD_5 remained between 13.2 and 26.6 mg O_2/L. Influent COD increased to 704.3 mg O_2/L in S2 2024, while

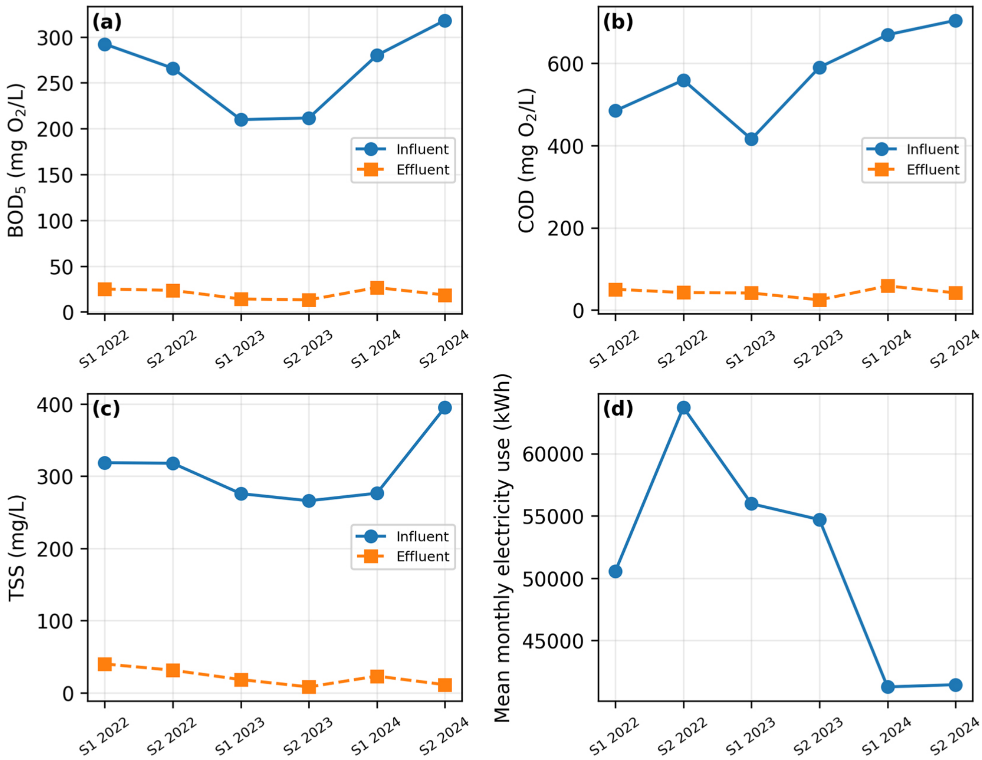

Figure 1. Semester-level variations in wastewater-quality parameters and mean monthly electricity use at AS-WWTP from S1 2022 to S2 2024: (a) influent and effluent BOD_5 concentrations; (b) influent and effluent COD concentrations; (c) influent and effluent TSS concentrations; (d) mean monthly electricity use

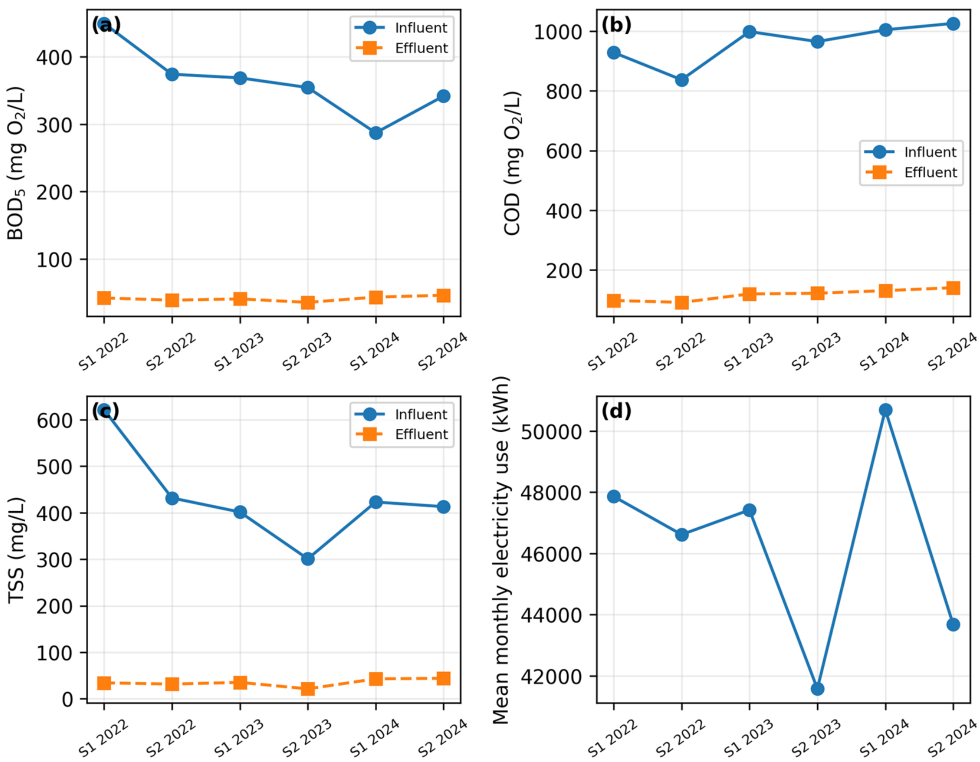

Figure 2. Semester-level variations in wastewater-quality parameters and mean monthly electricity use at TF-WWTP from S1 2022 to S2 2024: (a) influent and effluent BOD_5 concentrations; (b) influent and effluent COD concentrations; (c) influent and effluent TSS concentrations; (d) mean monthly electricity use

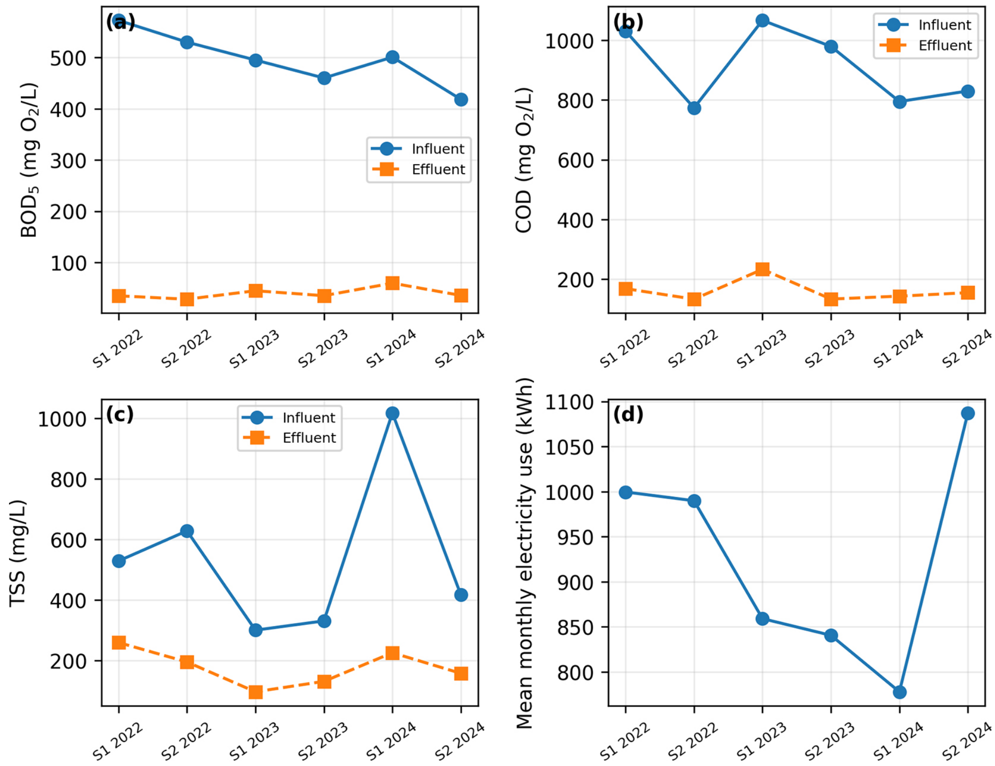

Figure 3. Semester-level variations in wastewater-quality parameters and mean monthly electricity use at NL-WWTP from S1 2022 to S2 2024: (a) influent and effluent BOD$_5$ concentrations; (b) influent and effluent COD concentrations; (c) influent and effluent TSS concentrations; (d) mean monthly electricity use

effluent COD remained below 60 mg O_2/L. Mean monthly electricity use declined to approximately 41,000 kWh during 2024.

At TF-WWTP, influent BOD$_5$ decreased from 449.1 mg O_2/L in S1 2022 to 287.1 mg O_2/L in S1 2024 before increasing to 341.5 mg O_2/L in S2 2024. Effluent BOD$_5$ remained within 35.8–46.5 mg O_2/L. Influent COD exceeded 1,000 mg O_2/L during 2024, whereas mean monthly electricity use remained within 41,575–50,692 kWh across semesters.

At NL-WWTP, influent BOD$_5$ decreased from 572.5 mg O_2/L in S1 2022 to 418.3 mg O_2/L in S2 2024. Effluent BOD$_5$ remained between 28.2 and 59.5 mg O_2/L. Influent TSS peaked at 1,017.3 mg/L in S1 2024, while effluent TSS remained comparatively elevated and variable. Mean monthly electricity use was substantially lower than at the other plants.

The three facilities also differed markedly in hydraulic throughput and influent mass loading. Over 2022–2024, TF-WWTP treated approximately 5.218 million m^3, compared with 2.838 million m^3 at AS-WWTP and 1.834 million m^3 at NL-WWTP, corresponding to mean observed influent flows of about 4.761, 2.589, and 1.674 m^3/d, respectively. Mean influent BOD$_5$ loads were approximately 1.721 kg/d for TF-WWTP, 671 kg/d for AS-WWTP, and 814 kg/d for NL-WWTP; the corresponding COD loads were 4.594, 1.453, and 1.513 kg/d, and TSS loads were 2.080, 787, and 901 kg/d. These differences provide important context for interpreting the energy- and removal-based comparisons.

Annual and overall treatment-performance metrics

Annual energy metrics are reported in Table 2, annual concentration-based removals in Table 3, and overall load-weighted indicators in Table 4. Figure 4 provides a direct comparison of energy intensity and load-weighted pollutant removal across the three configurations.

Across the complete study period, activated sludge achieved the strongest combined pollutant removal but also had the highest electricity intensity. Natural lagooning occupied the opposite end of the comparison, with extremely low electricity use but substantially weaker

Table 2. Annual energy metrics calculated from the monthly operating records

Station	Year	Electricity use (kWh)	Treated volume (m³)	SEC (kWh/m³)	kWh/kg BOD_5 removed
AS-WWTP	2022	685,555	932,865	0.735	2.826
AS-WWTP	2023	664,074	1,018,504	0.652	3.326
AS-WWTP	2024	496,482	886,320	0.560	2.030
TF-WWTP	2022	566,860	1,736,346	0.326	0.861
TF-WWTP	2023	533,967	1,674,416	0.319	0.977
TF-WWTP	2024	566,229	1,807,560	0.313	1.183
NL-WWTP	2022	11,936	500,424	0.024	0.046
NL-WWTP	2023	10,197	501,642	0.020	0.047
NL-WWTP	2024	11,190	832,424	0.013	0.032

Note: SEC: specific energy consumption. Treated volume is based on influent flow.

Table 3. Annual concentration-based removal efficiencies calculated from annual mean concentrations

Station	Year	BOD_5 removal (%)	COD removal (%)	TSS removal (%)
AS-WWTP	2022	91.31	91.12	88.83
AS-WWTP	2023	93.51	93.45	95.13
AS-WWTP	2024	92.46	92.70	94.90
TF-WWTP	2022	90.09	89.23	93.74
TF-WWTP	2023	89.37	87.63	91.94
TF-WWTP	2024	85.65	86.59	89.61
NL-WWTP	2022	94.30	83.30	60.62
NL-WWTP	2023	91.66	82.08	63.72
NL-WWTP	2024	89.66	81.66	73.19

Note: BOD_5 – five-day biochemical oxygen demand; COD – chemical oxygen demand; TSS – total suspended solids.

Table 4. Overall energy intensity and load-weighted pollutant removals for 2022–2024

Station	SEC (kWh/m³)	BOD_5 load removal (%)	COD load removal (%)	TSS load removal (%)	kWh/kg BOD_5 removed
AS-WWTP	0.651	93.39	93.52	93.90	2.688
TF-WWTP	0.319	89.24	88.59	92.41	0.990
NL-WWTP	0.018	92.37	83.28	67.26	0.040

Note: Load-weighted removals account for reported influent and effluent flow rates.

and more variable suspended-solids removal. The trickling filter retained high organic-matter and solids removal at approximately half the specific energy consumption of activated sludge. These results indicate a Pareto-type structure: improving one decision criterion generally required accepting a loss in another, and no configuration dominated all criteria simultaneously.

Exploratory comparison of monthly specific energy consumption

The monthly specific energy consumption distribution was highest at the activated-sludge plant (median 0.635 kWh/m³; interquartile range 0.556–0.715), intermediate at the trickling-filter plant (median 0.329 kWh/m³; interquartile range 0.282–0.365), and lowest at the natural-lagooning plant (median 0.019 kWh/m³; interquartile

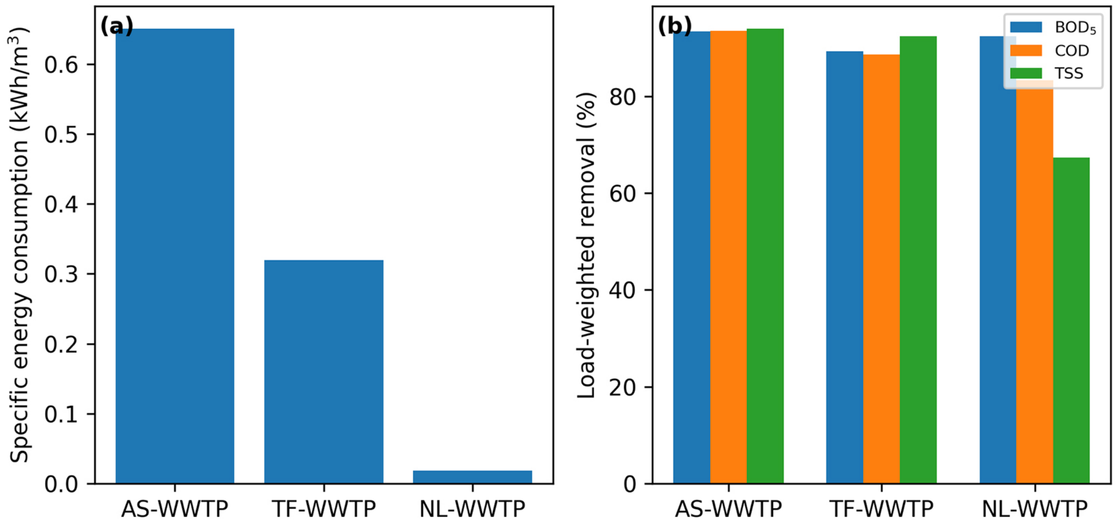

Figure 4. Comparison of overall energy intensity and load-weighted pollutant-removal performance for the three wastewater treatment plants over 2022–2024: (a) specific energy consumption; and (b) load-weighted removal of BOD_5, COD, and TSS

range 0.015–0.025). The Kruskal–Wallis test confirmed a significant difference among configurations ($H = 90.39$, $df = 2$, $p < 0.001$). All pairwise Mann–Whitney comparisons remained significant after Holm correction (adjusted $p < 0.001$). The magnitude and separation of the distributions show that the energy ranking was persistent rather than being driven by a small number of atypical months.

The quantitative stability analysis showed that TF-WWTP had the lowest effluent CVs for BOD_5, COD, and TSS (18.4%, 18.5%, and 30.4%, respectively). The corresponding CVs were 47.8%, 45.0%, and 93.5% for AS-WWTP and 47.3%, 27.9%, and 34.2% for NL-WWTP. Monthly SEC CVs were 21.0% for AS-WWTP, 43.2% for TF-WWTP, and 50.6% for NL-WWTP. Brown–Forsythe tests indicated no significant difference in BOD_5 dispersion among configurations ($F = 2.70$, $p = 0.072$), but significant differences for COD ($F = 15.21$, $p < 0.001$), TSS ($F = 44.05$, $p < 0.001$), and SEC ($F = 9.82$, $p < 0.001$). Holm-adjusted pairwise comparisons showed greater COD and TSS dispersion at NL-WWTP than at both mechanically treated configurations (adjusted $p < 0.001$); for SEC, NL-WWTP differed from AS-WWTP (adjusted $p < 0.001$) and TF-WWTP (adjusted $p = 0.005$), whereas AS-WWTP and TF-WWTP did not differ significantly in dispersion.

Qualitative Pareto interpretation

The joint interpretation of overall load-weighted removal, specific energy consumption, electricity per kilogram of five-day biochemical oxygen demand removed, and temporal variability produced three non-dominated decision positions. The resulting qualitative decision map is summarized in Table 5.

Table 5. Decision-oriented interpretation of the three wastewater-treatment configurations

Configuration	Primary strength	Main trade-off	Best-fit decision context	Decision position
Activated sludge	Highest combined pollutant removal and comparatively narrow effluent ranges	Highest electricity intensity	Strict effluent limits and strong operational control	Quality-priority position
Trickling filter	High removal with moderate electricity use	Slightly lower organic-matter removal than activated sludge	Balanced quality, cost, and operational simplicity	Balanced position
Natural lagooning	Minimum purchased electricity and high biodegradable-organic removal	Lower and more variable suspended-solids control	Land-available, energy-constrained communities	Energy-priority position

DISCUSSION

Process-specific performance and temporal variability

The activated-sludge configuration maintained the highest overall load-weighted removal for all three pollutants. Its comparatively narrow effluent ranges indicate strong process control despite variations in influent concentration. This behavior is consistent with the controllability of suspended-growth systems, where aeration and solids recirculation can buffer loading changes (Metcalf and Eddy/AECOM, 2014; Abusam et al., 2004). Aeration also explains the high electricity requirement reported in full-scale assessments (Longo et al., 2016; Panepinto et al., 2016). Comparable energy patterns have been reported for municipal plants with intensive aeration (He et al., 2019). Activated sludge should therefore be interpreted as a quality-priority configuration rather than an energy-efficient reference.

The trickling filter achieved robust pollutant removal at approximately 49% of the specific electricity demand of activated sludge. Its overall electricity use per kilogram of five-day biochemical oxygen demand removed was also markedly lower (0.990 versus 2.688 kWh/kg). This result is particularly relevant because it accounts for both treated volume and pollutant mass, reducing the risk of favouring a plant simply because it received weaker wastewater. Function-based normalization has been recommended for precisely this reason in wastewater energy benchmarking (Longo et al., 2019; Gallo et al., 2024). Under the studied operating conditions, the trickling filter offered the most balanced combination of removal performance, electricity demand, and temporal consistency.

Plant scale, hydraulic throughput, and influent strength can influence both apparent treatment performance and energy intensity. A larger treated volume can spread fixed pumping and auxiliary electricity demand over more cubic metres, while stronger influent wastewater increases the pollutant mass removed per unit volume and can reduce energy expressed per kilogram removed even when kWh/m^3 is unchanged. Hydraulic and mass loading can also affect oxygen demand, biofilm loading, hydraulic retention time, and solids separation. Accordingly, the use of specific energy consumption (kWh/m^3), load-weighted removal, and electricity per kilogram of BOD_5 removed reduces – but does not completely eliminate – the influence of scale and loading. The present findings should therefore be interpreted as full-scale operational benchmarks under the observed conditions rather than as controlled causal estimates attributable to treatment technology alone.

Natural lagooning required almost no purchased electricity and achieved high load-weighted removal of biodegradable organic matter. Its weaker total suspended solids performance reflects a known limitation of pond systems, where algal biomass, wind-driven resuspension, settling conditions, and hydraulic short-circuiting can increase effluent solids (Mara, 2013; Ho et al., 2017). Attached-growth interactions and seasonal biological activity can further alter pond behavior (Lian et al., 2022). Therefore, low electricity demand should not be interpreted as complete environmental superiority. Natural lagooning is most attractive where land is available and moderate effluent-solids variability can be managed through polishing or reuse-specific controls.

The variability indicators refine this interpretation of process stability. The trickling filter combined relatively low effluent CVs with robust absolute effluent quality, whereas the high relative TSS CV at AS-WWTP should be interpreted cautiously because it occurred around a low mean effluent concentration. Natural lagooning showed significantly greater COD and TSS dispersion than the two mechanically treated configurations, indicating greater sensitivity of discharge quality to changing operating and environmental conditions. Thus, stability is best assessed jointly from absolute effluent quality, CV, and formal dispersion tests rather than from CV alone.

Pareto trade-offs and technology-selection implications

The integrated comparison reveals three distinct decision zones. Activated sludge occupies the high-quality/high-energy end of the qualitative trade-off space; natural lagooning occupies the minimum-electricity/lower-solids-control end; and the trickling filter occupies an intermediate zone with no severe penalty in either dimension. This framework is more informative than a single composite score because it does not conceal the relative importance assigned by decision-makers to effluent limits, electricity cost, land availability, operator capacity, and process resilience. Multi-indicator benchmarking is recommended over universal rankings (Longo et al., 2016; Gallo et al., 2024). Context-specific technology selection is also emphasized in comparative assessments (Longo et al., 2019; Noyola et al., 2012). In practical terms, activated sludge is justified where strict and stable effluent quality is the dominant constraint; natural lagooning is justified where electricity and technical complexity must be minimized; and trickling filters are attractive where a balanced outcome is required.

Transferability, environmental relevance, and limitations

The proposed benchmark can be reproduced from variables routinely recorded by municipal operators and is therefore transferable to other plants with limited monitoring capacity. It is particularly relevant to semi-arid and water-scarce regions, where treated wastewater quality must be considered together with energy security and affordability. Nevertheless, the study is observational: the plants differed in scale, influent characteristics, design, and operating context, so process type cannot be isolated from all site effects. Monthly aggregation may also conceal short-duration failures, and temporal autocorrelation was not explicitly modelled. Electricity use represents only one component of environmental performance; direct methane and nitrous-oxide emissions, sludge management, land occupation, chemical use, and life-cycle construction impacts were not quantified. Life-cycle studies show that these omitted components can alter the environmental ranking of treatment alternatives (Corominas et al., 2013; Daskiran et al., 2022), while greenhouse-gas inventories require explicit consideration of direct process emissions (Intergovernmental Panel on Climate Change, 2019). The findings should therefore be used as an operational benchmark and decision framework, not as a universal life-cycle ranking.

CONCLUSIONS

The three full-scale wastewater-treatment configurations formed a clear quality–energy–variability trade-off over the 2022–2024 monitoring period. Activated sludge achieved the highest load-weighted removal of five-day biochemical oxygen demand, chemical oxygen demand, and total suspended solids, but it also had the highest specific electricity consumption. Natural lagooning minimized electricity use and maintained strong biodegradable organic-matter removal, while its suspended-solids removal was lower and more variable. The trickling filter preserved high pollutant removal at approximately half the energy intensity of activated sludge and therefore represented the most balanced configuration under the studied conditions. The qualitative Pareto interpretation showed that no technology simultaneously maximized effluent performance and minimized electricity demand. Integrating load-weighted removal, energy per treated volume, energy per pollutant mass removed, and temporal variability provides a more defensible basis for wastewater-treatment technology selection than ranking plants by removal percentage alone.

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