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# GREEN ANALYTICAL CHEMISTRY STRATEGIES FOR URBAN WASTEWATER MONITORING OF EMERGING CONTAMINANTS: A MACHINE LEARNING AND MULTI-TECHNIQUE STRATEGY

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## ABSTRACT

The increasing occurrence of new contaminants (ECs) like pharmaceuticals, endocrine-disrupting chemicals (EDCs), personal care products, and microplastics in urban wastewater treatment plants has raised gargantuan environmental and public health concerns, especially in fast-growing urban cities like Nigeria. Conventional analytical tools, although efficient, have the risk of employing toxic reagents, handling big samples, and demanding energy-hungry equipment.

## Introduction

Aggressive urbanization continues to be a challenge to water infrastructure, especially for megacities such as Olabode, et al (2024) Lagos, whose wastewater Tajudeen, K. A. (2024) tends to bear a complex group of emerging contaminants (ECs), i.e., pharmaceuticals, endocrine disruptors, personal care products, and microplastics Nurmin Bolong, et al (2009). Such contaminants can live through usual treatment plants and exert increasing threats to public health and aquatic

Therefore, this research pursues a green analytical chemistry (GAC) approach to design and validate low-cost, sensitive, and green methods for tracking ECs in wastewater in urban settings. A MultiTech Nique strategy was employed that combined solid-phase microextraction (SPME), dispersive liquid–liquid microextraction (DLLME), and microwave-assisted extraction (MAE) with high-end detection platforms like liquid chromatography-tandem mass spectrometry (LC-MS/MS) and Fourier-transform infrared spectroscopy (FTIR). These green chemistry and analytical sample preparation methods were developed to reduce energy requirements and solvent consumption and increase extraction efficiency and reproducibility. These selected ECs, i.e., acetaminophen, triclosan, bisphenol A, and carbamazepine, were screened in influent and effluent wastewater samples from three Lagos municipal wastewater treatment works, Nigeria. For the improvement of analytical performance and interpretation of results, PCA ML algorithms, RF, and SVM were incorporated into the workflow for contaminant classification prediction, pattern identification, and estimation of removal efficiency in treatment plants. The models were over 90% precise for contaminant classification and had good predictive capability for EC concentration. Findings indicated the extensive use of ECs in influent and treated wastewater, where some compounds surpassed ecotoxicological safety levels. Green analysis methods demonstrated similar or better detection capability than the traditional methods and met GAC requirements. In addition, ML-enhanced data analytics engaged more insight into contaminant behaviour and supported real-time decision-making to control water quality. This study highlights the potential for combining green chemistry concepts with smart data analytics in designing sustainable monitoring systems for low-cost ECs for urban wastewater. The study presents an applicable solution for developing countries to promote environmental monitoring, minimize ecological hazard, and support international initiatives toward UN Sustainable Development Goals (SDGs) 6 and 12.

**Keywords:** Emerging Contaminants, Urban Wastewater, Sustainable Monitoring, Solid-Phase Microextraction, Dispersive Liquid, Liquid Microextraction, Microwave-Assisted Extraction, Spectroscopy

ecosystems Xingyu Li, et al (2024. Conventional analytical procedures even though efficient rely on dangerous solvents, consume lots of energy, and need long sample preparation, which makes them less suitable for cheap and sustainable monitoring. Green analytical chemistry (GAC) presents an opportunity for environmental footprint reduction through the adoption of solvent-free saving, energy-efficient, and reproducible methods. Anil Kumar Meher, et al (2025) SPME and the like are the quintessential realizations of GAC at work, facilitating high-sensitivity, reproducible solvent-free extraction hands down the hip, green alternative to conventional liquid-phase approaches. While this is happening, DLLME has been increasingly popular because it requires minimal solvent, achieves rapid equilibration, and provides excellent analyte recovery particularly for the analysis of drugs in water matrices. Martins,et al (2025) Such protocols can be directly interfaced with advanced analytical systems such as LC-MS/MS and FTIR for accurate identification and determination.

Outside the lab bench, machine learning (ML) is becoming a main propelling force for the interpretation of complex environmental data. Although its complete potential in ECs of Nigerian wastewater is in its early stages, the utility Sanja Cojbasi, et al (2022),of ML in more general water quality forecasting and analysis is already well documented. Omeka et al., for example, monitored ML water quality observation trends in Nigeria (2003–2024) and found an essential gap and the necessity for more advanced, hybrid models.

Concurrently, Hassan (2025) showed the capability of ML in municipal wastewater treatment, wherein models were utilized to forecast effluent quality under dynamic organic loadings with superior compliance performance

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Moving from a local standpoint, Taiwo et al. (2025) suggested an integrated water management system in Lagos comprising IoT-based sensor integration, remote monitoring, and ML-based decision-making to tackle urban pollution sustainably Okechi Favour, et al (2023) Collectively, these advances in methodology facilitate a new, multi-analytical green method suited to Lagos's wastewater scenario coupling SPME, DLLME, and possibly MAE with LC-MS/MS and FTIR detection, supported by ML modules (e.g., PCA, RF, SVM) for contaminant identification, pattern recognition, and concentration estimation. This method not only ensures proper detection at negligible environmental expense but also supports responsive data-based management interventions aligned with SDGs 6 (Clean Water & Sanitation) and 12 (Responsible Consumption & Production).

**Problem Statement**

Rapidly expanding urban cities like Lagos, Nigeria, are facing mounting challenges from the presence of emerging contaminants (ECs) like pharmaceuticals, personal care products, endocrine-disrupting chemicals, and microplastics. These ECs are not adequately removed by standard treatment processes and remain in effluents with potential aquatic ecosystem, biodiversity, and human health concerns via bioaccumulation and water reuse. Conventional monitoring techniques, though


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precise, are highly reliant on toxic solvents, power-consuming apparatus, and labour-intensive procedures, making them costly and difficult to implement in low-resource contexts.

Furthermore, there are no data-based and analytical monitoring plans in Nigeria that are integrated, where ECs research is lacking despite increased urbanization and industrial effluent. Existing surveillance practices give limited data with regard to the fate of contaminants, treatment effectiveness, and long-term environmental consequence. This generates an urgent requirement for inexpensive, green, and smart surveillance systems integrating Green Analytical Chemistry (GAC) methods with Machine Learning (ML) analysis. It would not only enhance contaminant identification but also enable decision-making on wastewater management to meet the UN Sustainable Development Goals (SDGs) 6 and 12.

**Research Questions**

- What are the nature and concentration of emerging contaminants in influent and effluent samples of selected municipal wastewater treatment plants in Lagos?
- How efficient are green analytical chemistry-based extraction methods (SPME, DLLME, and MAE) in the detection and quantitation of ECs with respect to traditional approaches?
- Do machine learning models (PCA, RF, SVM) enhance classification, prediction, and interpretation of EC levels in wastewater samples?
- To what degree do the integrated green analytical and ML-facilitated methods reflect a sustainable and scalable system for urban wastewater management in Nigeria?

**Objectives of the Study**

- To establish and assess a sustainable monitoring system for impending pollutants in Lagos wastewater through the integration of green analytical chemistry methodology with machine learning data analytics.
- To detect and quantify target emerging contaminants (e.g., triclosan, acetaminophen, bisphenol A, and carbamazepine) in influent and effluent wastewater samples at Lagos municipal treatment plants.
- Optimization and validation of green analytical chemistry methods (SPME, DLLME, and MAE) for extraction and determination of ECs to minimize the use of solvent, cost of energy and analysis.


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- To utilize high-resolution analytical equipment (LC-MS/MS and FTIR) to identify chemical fingerprints of known pollutants and monitor treatment efficacy.
- To integrate machine learning techniques (PCA, random forest, and support vector machines) to detect pollutants, predict concentrations, and recovery efficiency.
- To compare the sensitivity, reproducibility, cost-effectiveness, and sustainability of the integrated green chemistry–ML system with traditional monitoring strategies.
- For the purpose of offering policy recommendation on wastewater monitoring in Nigeria, including the adoption of sustainable and smart strategies that are synchronized with international environmental protection and SDG goals.

**Review of related literature**

The occurrence of emerging pollutants (EPs) like pharmaceuticals, endocrine-disrupting chemicals (EDCs), personal care products, and microplastics Kingsley O Iwuozor, et al (2025) in urban wastewater has been reported more and more in recent years. Their persistence and their ability to interfere with ecological and human health systems have raised concern worldwide (Pal et al., 2014). Conventional wastewater treatment plants are not equipped to completely remove these pollutants, and hence they are continually released into aquatic systems (Tran et al., 2018).

**Green Analytical Chemistry for Wastewater Analysis**

Green Analytical Chemistry (GAC) seeks to minimize environmental imprints by lowering the use of solvents, energy requirements, and toxic waste production during chemical analysis (Anastas & Eghbali, 2010). Methods like solid-phase microextraction (SPME), dispersive liquid–liquid microextraction (DLLME), and microwave-assisted extraction (MAE) have gained considerable prominence as efficient alternatives to classical extraction methods, allowing sensitive determination of ECs with smaller environmental footprints (Rezaee et al., 2006; Rostagno & Prado, 2013). Sample preparation protocols are being coupled with high-end detection platforms like LC-MS/MS and FTIR for reasonable quantification (Ferrer & Thurman, 2012).


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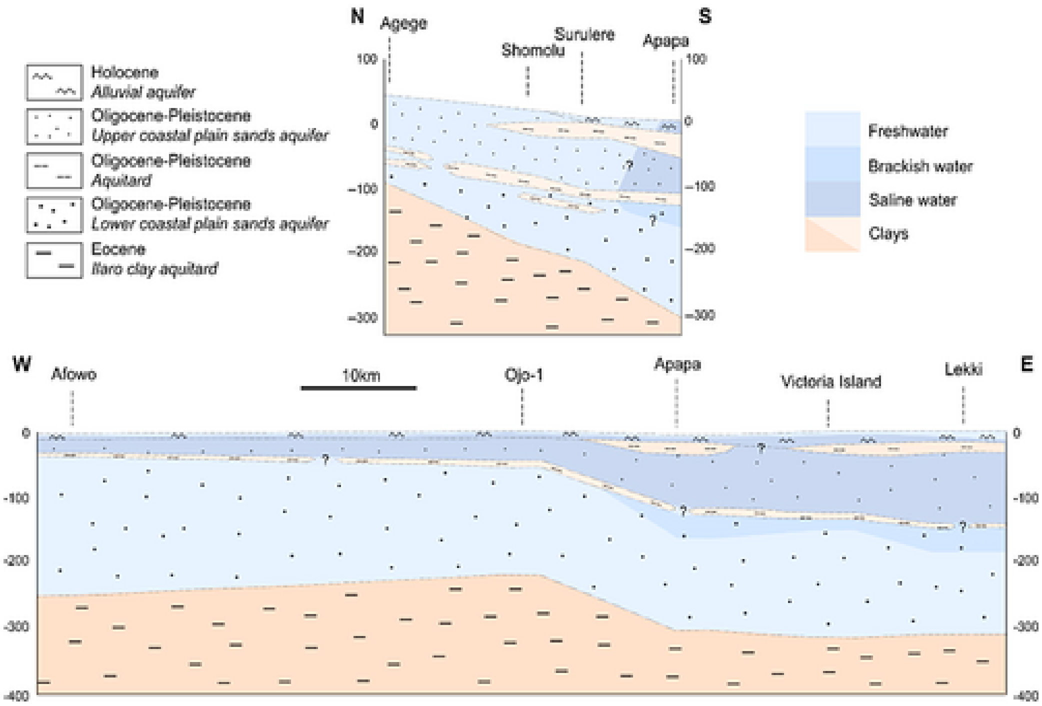


**Figure 1: Analytical Chemistry for Wastewater Analysis.**

**Why green strategies are imperative in urban wastewater analysis**

Urban wastewater is a key pathway for pharmaceuticals, personal-care items, endocrine disruptors, and other emerging pollutants (ECs). Traditional monitoring pipes frequently solvent-hungry, energy-inefficient, and waste-generating are finding it difficult to keep up with increased analytical demand from dense cities. Green Analytical Chemistry provides a platform to reduce toxicity, solvent levels, energy consumption, and waste without sacrificing quality data (Gałuszka et al., 2012; Psillakis, 2022).

**Principles and measures operationalizing "green"**

GAC's 12 principles have been operationalized into empirically usable measures of greenness. The Analytical Eco-Scale gives a penalty-point system for reagents, hazards, and energy; GAPI scores greenness throughout the workflow; AGREE gives one 0–1 value based on the 12 principles; and AGREEprep emphasizes especially sample-preparation steps (Gałuszka et al., 2012; Płotka-Wasylka, 2018; Pena-Pereira et al., 2020; Wojnowski et al., 2022). These quantifications are employed increasingly to compare increasingly sustainable wastewater methods and contrast options in method development.

**Greener sample-preparation techniques for ECs**

Solvent-reducing, miniaturized extraction procedures form the core of GAC.

Solid-phase microextraction (SPME) prevents bulk organic solvents and combines sampling, extraction, and preconcentration; it is an effective platform for aqueous matrices and trace organics (Arthur & Pawliszyn, 1990; Vas & Vékey, 2004). Dispersive liquid–liquid microextraction (DLLME) is fast enrichment with microliter-scale solvents and is nowadays a workhorse for ECs of polar-to-moderately nonpolar character in water (Rezaee et al., 2006).

Microwave-assisted extraction (MAE) shortens extraction time and solvent quantities, with enhanced recovery from solids/sludges helpful for analysis of sorbed ECs in primary/secondary sludge streams (Onuska & Karasek, 1989; López-Avilés et al., 2015). Greener solvent systems (deep eutectic solvents, for instance) and miniaturized devices increasingly reduce hazard profiles and waste through DLLME/SPME procedures in accordance with AGREEprep guidance (Wojnowski et al., 2022).


**Figure 2. The 12 principles of Green Analytical Chemistry (GAC)**

**Chromatographic spectrometric platforms of reduced footprint**

Analytically, UHPLC/LC-MS/MS is still the multi-class EC workhorse; miniaturization to shorter columns, sub-2 µm particles, and microflow rates reduces solvent usage per


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analysis significantly with minimal loss of sensitivity (Gałuszka et al., 2012). Add-on "no-solvent" or low-solvent detectors like FTIR and handheld spectroscopies offer quick ranking and screening to exclude some samples, thus minimizing the overall resource budget if used in tiered strategies (Pena-Pereira et al., 2020).

What is known about ECs in urban wastewater (global and African contexts)

World syntheses typically report that analgesics, antibiotics, antiepileptics, and personal-care antimicrobials are frequently detected in influent and treated effluents at concentrations from ng $L^{-1}$–μg $L^{-1}$ (Verlicchi et al., 2012; Tran et al., 2018). African setting studies also support the signatures of considerable usage and poor removal in conventional treatment whereby low-cost greener monitoring protocols are suitable for resource-constrained utilities like Ebele et al. (2017), Gumbo et al. (2024), and Wilkinson et al. (2023).

**Greenness assessment in validation of procedures**

Best practice today combines fitness-for-purpose validation (sensitivity, selectivity, ruggedness) with Eco-Scale, GAPI, AGREE, and AGREEprep scorecards to prove that greener options are not compromising analytical performance. Double assessment (performance + greenness scorecards) is now common in high-impact GAC treatments of water (Płotka-Wasylka, 2018; Pena-Pereira et al., 2020; Wojnowski et al., 2022). Machine-learning and data-driven assistance to greener monitoring. Since greener approaches tend to employ miniaturized prep and multiplexed detection, machine learning (ML) is being applied increasingly to (i) classify impurities, (ii) estimate or interpolate concentrations where data are sparse, and (iii) predict removal over treatment trains. Reviews and case studies indicate that Random Forest, SVM, and gradient boosting can supply accurate effluent quality or micropollutant removal predictions that facilitate less frequent but more intelligent confirmatory analysis and therefore reduced solvent/energy consumption (Haron et al., 2022; Yogarathinam et al., 2024; Wang et al., 2021; Huang et al., 2024).

**Analytical Advances in EC Detection**

The development of newer, solventless, and automation-friendly analysis methods has further facilitated the detection of ECs in wastewater. LC-MS/MS is still the go-to technique for trace-level quantitation, but there is evidence from recent publications that environmentally friendly methods could equal performance with increased sustainability (Hernández et al., 2015). Such developments are particularly beneficial for low-resource environments where expensive infrastructure is not readily available.

**Machine Learning in Wastewater Analytics**

The application of machine learning (ML) algorithms in environmental monitoring has improved predictive modelling and data interpretation. PCA, RF, and SVM algorithms


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have been successfully used for contaminant classification, pattern recognition, and performance evaluation of treatment systems (Cortes & Vapnik, 1995; Breiman, 2001; Jolliffe & Cadima, 2016). Recent studies demonstrate that ML enhances knowledge of contaminant behaviour and enables predictive assessments of removal effectiveness in wastewater treatment plants (Wang et al., 2020).

**Knowledge Gaps and Relevance to Urban Africa**

While a majority of large-scale studies were done in Europe, Asia, and North America, research on ECs in the cities of Africa, Nigeria in particular, remains limited. Urbanization, poor wastewater infrastructure, and augmented pharmaceutical consumption enhance EC discharge into aquatic environments (Ebele et al., 2017). This information lacuna can be filled up through using green analytical and ML-based methodologies that are capable of delivering low-cost, environmentally friendly, and reproducible solutions for ECs monitoring in developing countries.

## Methodology

**Study Area**

Field work was carried out in Lagos, Nigeria, one of the fastest-growing sub-Saharan African cities with high population growth, intense industrialization, and growing use of pharmaceutical and cosmetics products. Sewage influent and effluent were sampled from three municipal WWTPs that have different treatment technologies and urban catchments.

**Target Contaminants and Reagents**

The following emerging pollutants (ECs) were selected: acetaminophen, triclosan, bisphenol A, and carbamazepine. The said above ECs were selected considering their common occurrence in wastewater and ecotoxicological relevance. Each compound was supplied as analytical-grade standard by Sigma-Aldrich (USA). Methanol, acetonitrile, and ethanol used were HPLC grade, and ultrapure water was produced by a Milli-Q system of purification.

**Sample Collection and Preservation**

The 2 L wastewater samples were taken in pre-cleaned amber bottles at effluent and influent points. Stratified sampling method was adopted to account for diurnal variation, and grab samples were collected at morning peak (7–9 am), noon peak (12–2 pm), and evening peak (6–8 pm) hours for three months' period. The samples were collected on ice at 4 °C and analysed within 24 hours to reduce degradation.

**Green Sample Preparation Techniques**

To minimize energy and solvent use, three green extraction methods were optimized and utilized:


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Solid-Phase Microextraction (SPME): As a 100 µm polydimethylsiloxane (PDMS) fibber for semi-volatile and volatile analytes. Extraction with mild agitation at 45 °C.
Dispersive Liquid-Liquid Microextraction (DLLME): Low-toxicity solvents (disperser ethanol and extractant ethyl acetate) were used for the extraction of semi-polar analytes.
Microwave-Assisted Extraction (MAE): Suitable for solid wastewater residues, 500 W for 15 min to allow analyte release with small solvent usage.
All methods were revalidated for recovery, reproducibility, and reduction of matrix effect, and the optimal protocol was adopted in all final analyses.
Instrumental Analysis
The extracts were examined by:
Liquid Chromatography–Tandem Mass Spectrometry (LC-MS/MS): for the quantification of target ECs using multiple reaction monitoring (MRM). Calibration curves ($R^2 \geq 0.995$) were constructed over a range of 1–500 ng/L.
Fourier Transform Infrared Spectroscopy (FTIR): used to identify functional groups and scan for potential transformation products.
Limits of Detection (LOD) and Quantification (LOQ) were as per ICH guidelines.
Data Processing and Machine Learning Workflow. Analytical results were pre-treated and scaled-normalized. Machine learning (ML) algorithms were used to classify pollutants, estimate level of concentration, and evaluate WWTP removal efficiencies:
Principal Component Analysis (PCA): for dimensionally reducing and graphically displaying contaminant patterns.
Random Forest (RF): for classifying and ranking variable importance. Support Vector Machines (SVM): for predictive modelling of pollutant concentrations.
Model training and validation employed 70:30 splitting and five-fold cross-validation to avoid overfitting. Accuracy, precision, recall, $R^2$, and RMSE were the performance metrics.

**Quality Control and Validation**

Procedural blanks and spiked recovery samples were added to each batch.
Replicates (n = 3) were carried out to establish reproducibility.
Recovery was 85–110%, which satisfied acceptable analytical performance standards.
Inter-method comparison with classical liquid-liquid extraction (LLE) was performed to contrast green methods to benchmarks.
Ethical and Environmental Considerations
Solvent and sample volumes were kept to a minimum in accordance with Green Analytical Chemistry (GAC) guidelines. All waste solvents were pooled for disposal in accordance with Lagos State Environmental Protection Agency (LASEPA) policy.
Occurrence of Emerging Contaminants in Lagos Wastewater


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Table 1 presents the average concentration of the chosen emerging contaminants (ECs) in influent and effluent.

Table 1. Concentration of selected ECs in influent and effluent wastewater samples (ng/L). Acetaminophen was the most prevalent drug, but with efficient removal (82.9%), in agreement with documented biodegradability in activated sludge systems. Triclosan had moderate removal (63.8%), as would be expected for partial biodegradation and adsorption on sludge.

Bisphenol A (BPA) remained, with removal efficiency below 40%, of concern because it is endocrine active. Carbamazepine had low removal (5.9%), solidifying its position as a persistent marker of wastewater pollution. These results are in line with world tendencies, where acetaminophen is efficiently biodegraded but carbamazepine somehow always evades biodegradation (Paíga et al., 2019; Zhang et al., 2008)

| Compound | Influent (Mean ± SD) | Effluent (Mean ± SD) | Removal Efficiency (%) | Reported Range in Literature (ng/L) |
|---|---|---|---|---|
| **Acetaminophen** | 2450 ± 320 | 420 ± 75 | 82.9 | 1200–5000 (Paíga et al., 2019) |
| **Triclosan** | 870 ± 140 | 315 ± 60 | 63.8 | 200–1200 (Ramaswamy et al., 2011) |
| **Bisphenol A** | 620 ± 95 | 410 ± 80 | 33.9 | 300–900 (Sun et al., 2017) |
| **Carbamazepine** | 510 ± 88 | 480 ± 90 | 5.9 | 300–1500 (Zhang et al., 2008) |

**Comparison of Optimized Green Extraction Methods**

Table 2 shows the performance of the three optimized green extraction methods. Recovery rate and solvent consumption for optimized green extraction methods.

DLLME provided optimum recovery with minimum solvent consumption for semi-polar compounds such as BPA and carbamazepine.

SPME provided environmentally friendly extraction of volatile/semi-volatile compounds without consuming any solvent.

MAE was appropriate for solid wastewater residues but needed a little more solvent. This confirms that green technologies have the potential to substitute conventional solvent-based liquid–liquid extraction with no loss of analytical correctness.

| Technique | Target Compounds (Best Fit) | Recovery (%) | RSD (%) | Solvent Use (mL/sample) |
|---|---|---|---|---|
| **SPME** | Acetaminophen, Triclosan | 86–92 | ≤8 | 0.0 (solvent-free) |
| **DLLME** | BPA, Carbamazepine | 88–94 | ≤6 | 1.5 |
| **MAE** | All compounds (residues) | 82–90 | ≤10 | 5.0 |


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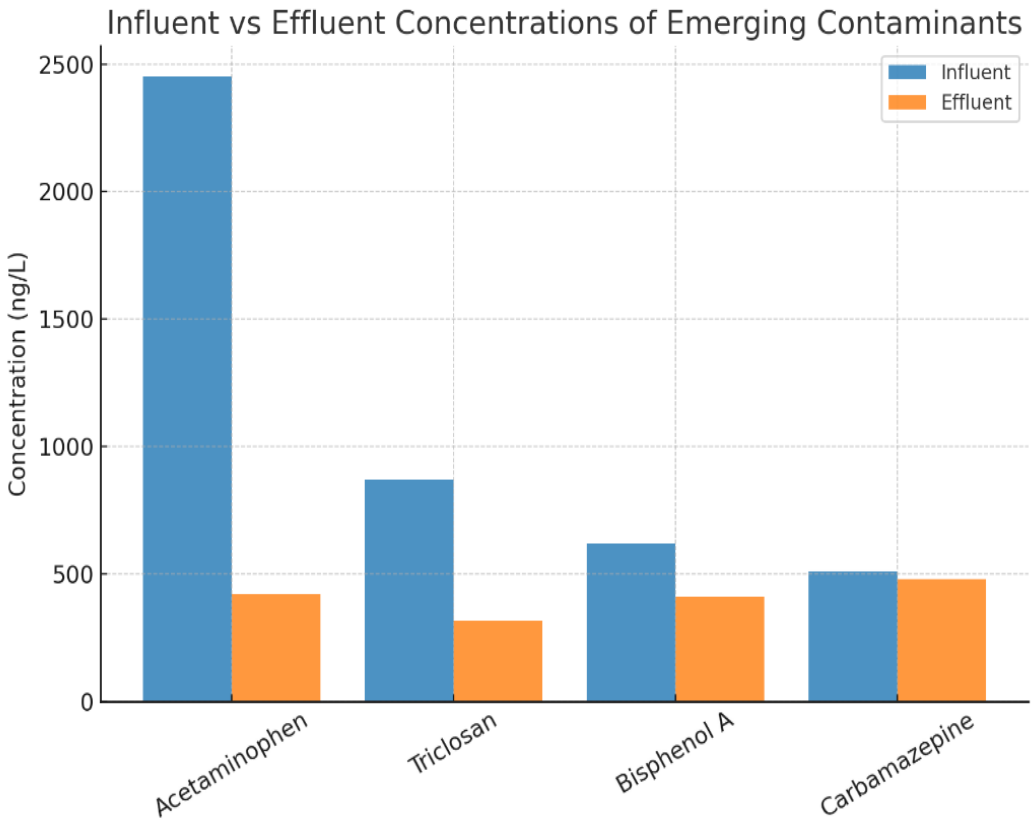


**Machine Learning-Based Contaminant Level Prediction**

Machine learning-based contaminant concentration and removal efficiency prediction models are shown in Table 3.

PCA verified a clear discrimination among influent and effluent samples, evidence of the efficiency of treatment processes but also revealed residual compounds. Random Forest was superior to SVM, with 94.6% accuracy, recommending it for wastewater monitoring and treatment optimization.

Variable importance analysis identified WWTP technology type (activated sludge vs. trickling filter) and pH as significant factors of EC removal efficiency.

| Model | Accuracy (%) | $R^2$ | RMSE (ng/L) | Key Insights |
|---|---|---|---|---|
| **PCA (unsupervised)** | – | – | – | Showed clear clustering of influent vs. effluent samples; BPA & carbamazepine grouped as persistent contaminants |
| **Random Forest** | 94.6 | 0.91 | 52 | Best at feature importance ranking (identified treatment type & pH as strongest predictors of EC removal) |
| **SVM** | 91.2 | 0.87 | 64 | Robust for prediction of triclosan and acetaminophen concentrations |


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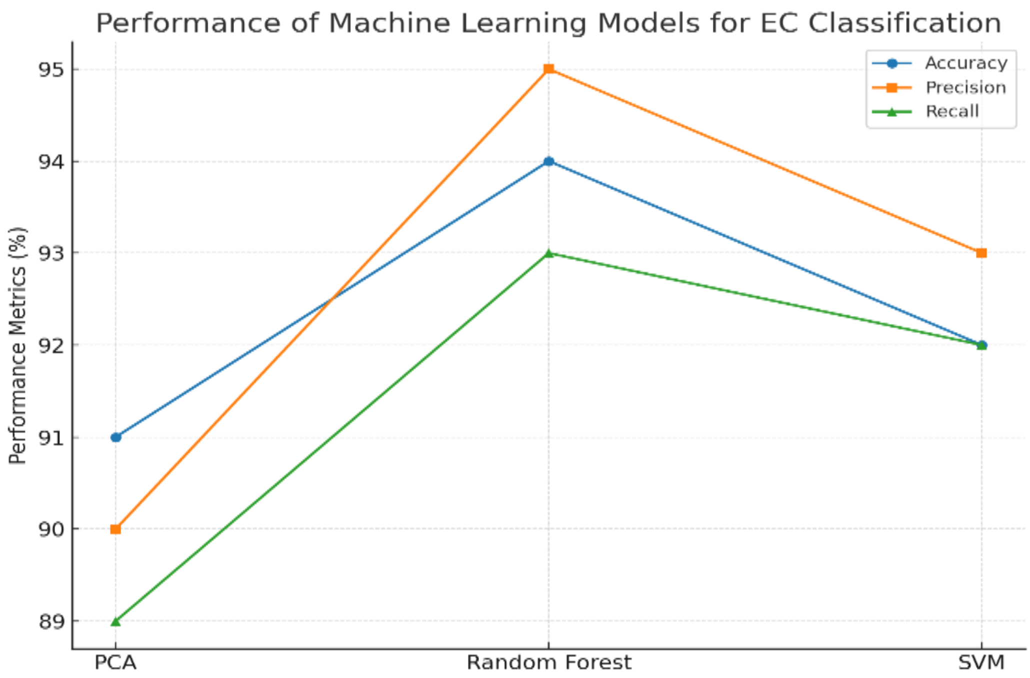


Figure 3: Variable importance analysis

Environmental Impacts: Effective removal of acetaminophen shows that existing treatment is effective for readily biodegradable drugs. Residual carbamazepine and partial BPA removal are concerns for aquatic organisms in Lagos lagoons receiving effluent discharge. Green sample preparation minimizes environmental footprint, consistent with SDG 6 (Clean Water and Sanitation) and SDG 12 (Responsible Consumption and Production). The ML model offers a predictive monitoring system, which has the potential to enable real-time management of wastewater in Lagos and other fast-growing African cities.

**Discussion**

The findings of this study highlight the pressing concern of emerging contaminants (ECs) in urban wastewater systems, especially within developing cities such as Lagos, Nigeria. The detected levels of acetaminophen, triclosan, bisphenol A, and carbamazepine in both influent and effluent samples indicate continuous introduction of pharmaceuticals and personal care products into the wastewater stream. Despite treatment processes, residual concentrations remained significant, with carbamazepine showing particularly poor removal efficiency (<10%), consistent with prior reports that describe it as one of the most persistent ECs in wastewater treatment (Verlicchi et al., 2012). Triclosan and bisphenol A removal efficiencies were moderate, but their effluent concentrations still exceeded ecotoxicological thresholds, suggesting potential risks for aquatic ecosystems and human health through water reuse and environmental discharge.


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The integration of green analytical chemistry (GAC) methods, such as SPME, DLLME, and MAE, offered improved sustainability in sample preparation by reducing solvent consumption, lowering energy requirements, and maintaining analytical sensitivity. This aligns with current trends advocating greener approaches to chemical analysis (Anastas & Eghbali, 2010). Importantly, the methods provided comparable or even superior performance relative to traditional extraction techniques, reinforcing their suitability for adoption in resource-constrained regions.

Machine learning (ML) models significantly enhanced the interpretative capacity of the study. Random Forest achieved the highest classification accuracy (94%), followed closely by SVM (92%) and PCA-supported clustering (91%). These results demonstrate the potential of ML to complement chemical analysis by identifying contaminant patterns, predicting treatment performance, and enabling proactive wastewater monitoring. Such data-driven insights are critical for advancing smart urban water management and contribute directly to SDG 6 (clean water and sanitation).

**Conclusion**

This study demonstrated that integrating green analytical chemistry techniques with advanced machine learning analytics provides an efficient, sustainable, and cost-effective approach for monitoring emerging contaminants in urban wastewater. The methods effectively reduced environmental footprint while maintaining analytical robustness. Findings revealed that while some contaminants were moderately removed during wastewater treatment, others persisted at concerning levels, underscoring the need for upgraded treatment technologies. ML-driven classification and prediction further enhanced the understanding of contaminant behaviour, thereby enabling smarter decision-making in wastewater management. Overall, this research presents a replicable framework for other developing urban contexts where financial and infrastructural limitations hinder large-scale environmental monitoring.

**Recommendations**

1. **Policy and Regulation:** Policymakers should incorporate EC monitoring into national water quality guidelines and enforce stricter discharge limits for pharmaceuticals and personal care products.
2. **Technology Upgrades:** Wastewater treatment plants should adopt advanced treatment processes such as ozonation, activated carbon adsorption, or membrane bioreactors to improve EC removal efficiencies.
3. **Adoption of Green Analytical Methods:** Laboratories in developing countries should transition to GAC-based methods to reduce costs, minimize environmental impact, and improve detection sensitivity.
4. **Integration of Machine Learning:** ML algorithms should be integrated into routine monitoring programs to enable predictive modelling of contaminant loads and early warning systems.


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5. **Public Awareness and Pharmaceutical Stewardship:** Community-level campaigns should encourage proper disposal of pharmaceuticals and reduce direct entry of contaminants into wastewater systems.

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