American Journal of Advanced Technology and Engineering Solutions

Volume: 3; **Issue:** 2
Pages: 33-77
eISSN: 3067-5146

Machine Learning–Based Assessment of Environmental and Public Health Risks in Sewerage Sludge Management Systems

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Doi: 10.63125/y3yfxa92
Received: 09 January 2023; **Revised:** 10 February 2023; **Accepted:** 22 March 2023; **Published:** 05 June 2023;

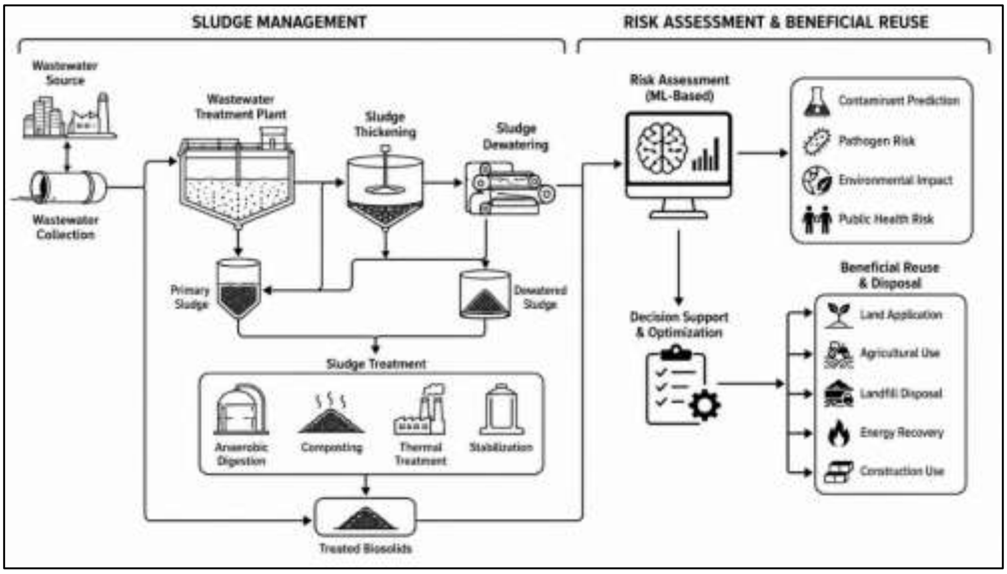
Abstract
This quantitative study examined machine learning–based assessment of environmental and public health risks in sewerage sludge management systems using sludge quality measurements, contaminant concentration data, treatment performance indicators, and public health risk variables. The study adopted a quantitative predictive design and analyzed a final dataset of 250 observations collected from selected sludge management facilities after 18 incomplete records and 7 duplicate observations were removed during data screening. Descriptive analysis showed substantial variation across the measured variables, with mean heavy metal concentration recorded at 178.42 mg/kg, mean organic pollutant concentration at 91.35 mg/kg, mean moisture content at 68.52%, and mean treatment efficiency at 83.67%. The average environmental risk score was 61.24, while the mean public health risk index was 58.13, indicating moderate overall risk across the sampled facilities. Comparative analysis across sludge treatment categories showed that primary sludge produced the highest mean environmental risk score at 72.45, whereas treated biosolids produced the lowest mean score at 47.63. Regression analysis demonstrated that treatment efficiency, heavy metal concentration, pathogen indicator score, and organic pollutant concentration were significant predictors of environmental and public health risk outcomes. The model explained 74.2% of the variance in risk scores, confirming strong predictive power. Machine learning analysis indicated that the Random Forest model achieved the highest predictive performance, with 93.8% testing accuracy, 92.6% precision, 94.2% recall, an F1-score of 93.4%, and an AUC of 0.961. Artificial Neural Network and Support Vector Machine models also demonstrated strong performance, with testing accuracies of 91.7% and 89.9%, respectively. Feature importance analysis identified treatment efficiency as the strongest predictor, contributing 28.4% to model performance, followed by heavy metal concentration at 24.7% and pathogen indicator score at 18.3%. Overall, the findings confirmed that machine learning models provided reliable quantitative tools for classifying environmental and public health risks in sewerage sludge management systems.

Keywords
Machine Learning, Sewerage Sludge, Environmental Risk Assessment, Public Health Risk, Predictive Analytics.

INTRODUCTION

Sewerage sludge management refers to the collection, treatment, processing, transportation, disposal, and beneficial reuse of the semi-solid residual material generated during municipal and industrial wastewater treatment processes. Sewerage sludge, often referred to as biosolids after appropriate treatment, contains a complex mixture of organic matter, nutrients, microorganisms, heavy metals, pharmaceutical residues, endocrine-disrupting compounds, microplastics, and other contaminants that originate from domestic, commercial, agricultural, and industrial activities (Heo et al., 2021).

Figure 1: Sewerage sludge management and reuse process

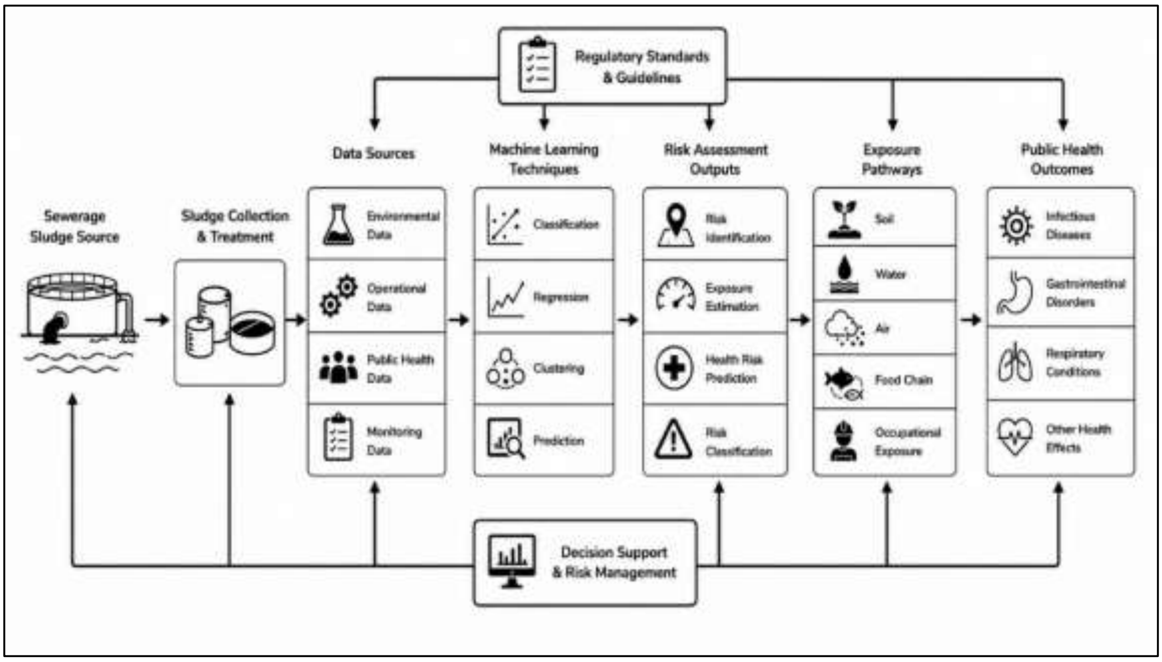


The management of this material has become a significant environmental and public health concern due to increasing urbanization, industrial expansion, and population growth across developed and developing nations. International organizations have emphasized the importance of sustainable sludge management because inadequate handling practices can contribute to soil contamination, groundwater pollution, surface water degradation, atmospheric emissions, and human exposure to hazardous substances. Consequently, sewerage sludge management systems represent a critical component of modern sanitation infrastructure and environmental protection strategies. The growing complexity of sludge composition has generated substantial challenges for environmental monitoring and risk assessment. Conventional assessment approaches often rely on laboratory analyses, deterministic models, and periodic inspections that may not adequately capture the dynamic interactions among biological, chemical, and environmental variables. Sewerage sludge contains thousands of potentially harmful constituents whose concentrations fluctuate across treatment stages and geographic regions (Sundui et al., 2021). Variations in treatment technologies, climatic conditions, industrial discharge patterns, and population behaviors further increase uncertainty in environmental and public health evaluations. Quantitative assessment methods have therefore become essential for understanding the relationships between contamination sources, treatment efficiency, pollutant persistence, ecological exposure pathways, and human health outcomes. Advanced analytical approaches facilitate the identification of patterns and correlations that are difficult to detect using traditional statistical techniques alone. Machine learning represents a branch of artificial intelligence that enables computer systems to learn from data and improve predictive performance without explicit programming for every analytical task. Machine learning algorithms identify hidden structures, classify observations, estimate risk probabilities, and generate predictive models from large datasets. In environmental management contexts, machine learning techniques have demonstrated substantial capability in handling nonlinear relationships, multidimensional datasets, and complex interactions among variables (Yang et al., 2021). The integration of machine learning into sewerage sludge management provides opportunities to evaluate contamination levels, predict environmental impacts, estimate

pathogen occurrence, assess treatment effectiveness, and quantify public health risks with enhanced precision. Quantitative frameworks supported by machine learning methodologies can process extensive monitoring data derived from sensors, laboratory measurements, treatment facilities, and environmental surveillance systems. Such capabilities support evidence-based understanding of sludge-related risks across diverse environmental settings and population groups. The international relevance of these analytical developments reflects increasing governmental and institutional efforts to improve wastewater sustainability, protect ecosystem integrity, and strengthen public health protection through data-driven environmental management systems (Cheng et al., 2020).
The global expansion of wastewater treatment infrastructure has resulted in unprecedented growth in sewerage sludge production. Rapid urbanization, industrial development, and improvements in sanitation services have increased the volume of sludge generated by treatment facilities worldwide. Municipal wastewater treatment plants produce millions of tons of sludge annually, creating significant challenges regarding storage, treatment, transportation, and final disposal. The environmental significance of sludge management extends beyond waste handling because sludge serves as a reservoir of nutrients, organic compounds, pathogens, trace elements, and emerging contaminants. Its composition directly influences soil quality, water resources, biodiversity, and ecosystem stability when released into the environment through land application, landfill disposal, incineration, or accidental discharge (Latosińska et al., 2021). Consequently, sludge management occupies a central position within global environmental governance and sustainable development initiatives. Environmental risks associated with sludge management emerge through multiple pathways. Heavy metals such as cadmium, chromium, lead, mercury, and arsenic may accumulate in agricultural soils following repeated sludge application. Persistent organic pollutants, pharmaceutical compounds, antibiotic residues, and microplastics can remain in treated sludge and subsequently enter terrestrial and aquatic ecosystems. These contaminants may alter microbial communities, affect nutrient cycling processes, reduce soil productivity, and disrupt ecological balance. Surface runoff and leaching mechanisms facilitate the movement of pollutants into rivers, lakes, and groundwater systems, thereby expanding the geographical scope of environmental exposure (El-Rawy et al., 2021). Air emissions generated during sludge treatment and disposal activities may also contribute to odor nuisance, greenhouse gas emissions, and atmospheric contamination. Such interconnected environmental impacts illustrate the complexity of sludge-related risk management and highlight the need for comprehensive assessment methodologies. Environmental monitoring programs generate substantial quantities of data related to sludge composition, pollutant concentrations, treatment performance, meteorological conditions, and ecological indicators. The multidimensional nature of these datasets presents analytical challenges that conventional methods may struggle to address efficiently (Przydatek & Wota, 2019). Machine learning algorithms provide advanced capabilities for processing environmental information characterized by high dimensionality, temporal variability, and nonlinear relationships. Predictive modeling techniques can identify contamination hotspots, classify environmental risk levels, estimate pollutant transport patterns, and evaluate treatment outcomes under varying operational conditions. Quantitative machine learning frameworks enable environmental managers to extract meaningful insights from large-scale datasets while supporting systematic evaluation of sludge management systems. The increasing availability of environmental monitoring technologies, remote sensing platforms, sensor networks, and digital reporting systems has further strengthened the applicability of machine learning approaches in environmental risk assessment. These developments have transformed sludge management research into a data-intensive field requiring sophisticated computational tools capable of supporting accurate and scalable environmental analysis (Hwangbo et al., 2021).
Public health risk assessment constitutes a fundamental aspect of sewerage sludge management because sludge contains biological, chemical, and physical hazards capable of affecting human populations through multiple exposure pathways. Human contact with contaminated sludge may occur directly through occupational activities or indirectly through food chains, water resources, air emissions, and environmental media. Pathogenic microorganisms present in untreated or inadequately treated sludge include bacteria, viruses, protozoa, helminths, and antibiotic-resistant organisms. Exposure to these contaminants may contribute to infectious diseases, gastrointestinal disorders,

respiratory conditions, and other adverse health outcomes. Chemical contaminants such as heavy metals, pharmaceutical residues, endocrine-disrupting compounds, and persistent organic pollutants further increase concerns regarding long-term health effects (Bagherzadeh et al., 2021).

Figure 2: Sewerage sludge risk assessment framework



As wastewater treatment systems continue to expand globally, understanding and quantifying these health risks has become increasingly important for regulatory agencies, environmental authorities, and public health institutions. The complexity of public health assessment in sludge management arises from the interaction of numerous variables operating across environmental and social systems. Population density, occupational exposure, sanitation infrastructure quality, treatment technology effectiveness, climate variability, land-use practices, and socioeconomic conditions all influence health risk distributions. Traditional epidemiological and environmental health approaches provide valuable information regarding exposure and disease relationships; however, the increasing volume of environmental and health data requires analytical methods capable of integrating diverse information sources. Public health surveillance systems, wastewater monitoring programs, clinical databases, laboratory analyses, and environmental measurements collectively generate large datasets that contain valuable insights regarding risk patterns and exposure dynamics (Zeinolabedini & Najafzadeh, 2019). Quantitative assessment frameworks must therefore address challenges associated with data heterogeneity, uncertainty, temporal variation, and spatial complexity. Machine learning techniques offer advanced solutions for analyzing public health risks associated with sewerage sludge management systems. Classification algorithms can identify high-risk populations and contaminated locations, while regression models estimate exposure levels and health outcome probabilities. Clustering techniques facilitate the detection of hidden patterns among environmental and epidemiological variables, enabling more detailed characterization of risk profiles (Harrou et al., 2018). Predictive analytics can support evaluation of pathogen occurrence, contaminant persistence, and population vulnerability across diverse geographic settings. These computational methods enhance the capacity of quantitative research to examine relationships among environmental conditions, treatment processes, contaminant concentrations, and public health indicators. The integration of machine learning into public health risk assessment reflects broader international efforts to strengthen evidence-based environmental health management through advanced data analytics. Growing recognition of environmental determinants of health has reinforced the importance of developing robust quantitative frameworks capable of supporting comprehensive assessment of sewerage sludge management

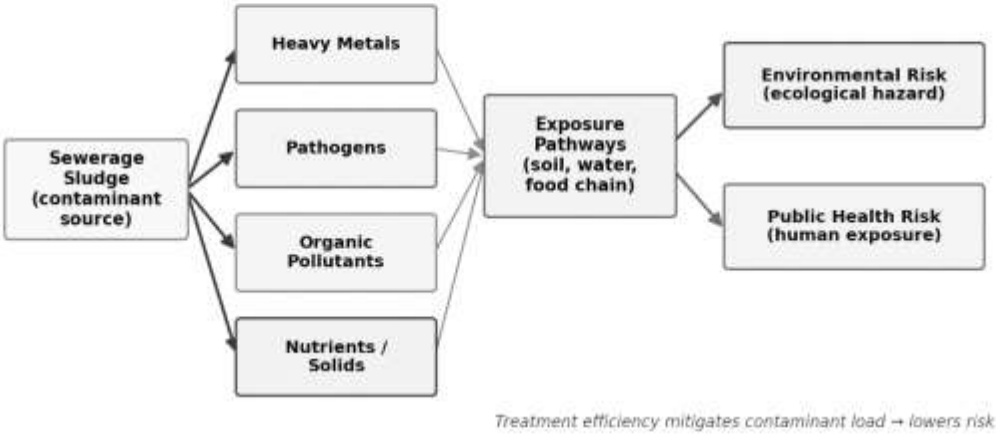
systems and their implications for human well-being (Mamandipoor et al., 2020).
Machine learning has emerged as one of the most influential computational approaches for analyzing complex environmental systems characterized by large datasets, multiple interacting variables, and nonlinear relationships. Environmental risk assessment traditionally relies on statistical analyses, deterministic models, and expert-based evaluations to estimate the likelihood and severity of ecological hazards. The increasing complexity of environmental challenges associated with wastewater treatment and sewerage sludge management has created a demand for analytical tools capable of processing vast amounts of heterogeneous information. Machine learning addresses this requirement by enabling automated pattern recognition, classification, prediction, and optimization based on observed data (Nair & Vijaya, 2021). The methodology encompasses a broad range of algorithms, including supervised learning, unsupervised learning, ensemble learning, neural networks, support vector machines, decision trees, random forests, and deep learning architectures. These techniques allow researchers to uncover hidden relationships among environmental indicators and generate predictive insights from multidimensional datasets. Environmental risk assessment in sewerage sludge management involves the evaluation of pollutant concentrations, contaminant transport mechanisms, treatment performance indicators, exposure pathways, and ecological outcomes. Each of these dimensions produces substantial quantities of numerical information collected from monitoring programs, laboratory analyses, field observations, and operational records. Traditional analytical methods often encounter limitations when handling nonlinear interactions among environmental variables, particularly when pollutant behavior is influenced by changing climatic conditions, treatment technologies, and site-specific characteristics (Kang et al., 2020). Machine learning algorithms offer enhanced flexibility by learning directly from empirical observations and continuously improving predictive performance through iterative optimization processes. Such capabilities are especially valuable in sludge management systems where contaminant distributions and environmental responses exhibit considerable variability across geographic regions and operational contexts. The application of machine learning in environmental risk assessment also facilitates the integration of diverse datasets originating from different sources and scales. Environmental monitoring networks, wastewater treatment facilities, remote sensing technologies, and geographic information systems generate information that can be combined within machine learning frameworks to support comprehensive risk evaluation. Through predictive modeling, machine learning can identify contamination hotspots, estimate pollutant mobility, classify environmental vulnerability zones, and evaluate treatment effectiveness under varying operational conditions (Farhi et al., 2021). These analytical functions contribute to a more detailed understanding of the environmental dynamics associated with sewerage sludge management systems. As environmental monitoring technologies continue to generate increasingly complex datasets, machine learning has become an essential quantitative tool for transforming raw environmental information into actionable risk indicators that support rigorous scientific investigation and evidence-based environmental assessment.
Quantitative assessment of sewerage sludge management systems depends heavily on the availability and quality of environmental, operational, and public health data. Modern wastewater treatment facilities generate extensive datasets describing sludge composition, treatment efficiency, contaminant concentrations, nutrient content, microbial activity, energy consumption, and disposal outcomes (Nielsen & Stefanakis, 2020). Additional information is obtained from environmental monitoring programs that measure soil quality, groundwater contamination, surface water conditions, atmospheric emissions, and ecosystem responses. Public health datasets further contribute information regarding disease prevalence, exposure indicators, occupational safety records, and community health outcomes. The integration of these diverse information sources creates opportunities for comprehensive quantitative analysis while simultaneously introducing challenges related to data complexity, variability, and uncertainty. Sewerage sludge datasets often contain hundreds of variables measured across different spatial and temporal scales. Concentrations of heavy metals, organic pollutants, pathogens, nutrients, and emerging contaminants may fluctuate according to seasonal patterns, industrial discharges, treatment technologies, and climatic conditions. Such variability creates intricate relationships that are difficult to characterize using conventional analytical approaches (Liu et al., 2021). Quantitative modeling techniques are therefore essential for identifying statistically

significant associations among variables and estimating the influence of individual factors on environmental and health outcomes. Machine learning methodologies provide advanced mechanisms for handling high-dimensional datasets by automatically identifying relevant predictors, reducing analytical complexity, and improving model performance through data-driven learning processes. The effectiveness of quantitative risk assessment depends not only on the volume of available data but also on the ability to transform information into meaningful indicators of environmental and public health risk. Feature selection methods, dimensionality reduction techniques, classification algorithms, and predictive models facilitate the extraction of relevant patterns from large datasets while minimizing analytical noise (Jeon et al., 2021). These methods enable researchers to evaluate contaminant behavior, treatment performance, exposure probabilities, and risk distributions within sludge management systems. Quantitative modeling also supports comparative analysis across treatment facilities, geographic regions, and operational conditions, thereby improving understanding of factors that contribute to environmental degradation and human exposure. The combination of large-scale environmental datasets and machine learning methodologies provides a powerful framework for examining complex sludge management systems through systematic and statistically robust analytical procedures.

Environmental and public health risks associated with sewerage sludge management are closely linked to the pathways through which contaminants move from treatment systems into ecological and human environments. Exposure pathways represent the mechanisms by which hazardous substances are transferred from sludge sources to environmental receptors and ultimately to human populations (Chowdhury et al., 2021). These pathways include soil contamination, groundwater infiltration, surface water runoff, atmospheric dispersion, food chain accumulation, and direct occupational exposure. The movement of contaminants through these interconnected systems creates complex patterns of environmental interaction that require detailed quantitative analysis to understand fully. Effective risk assessment therefore depends on the identification and characterization of exposure routes that contribute to ecological degradation and adverse health outcomes. Sewerage sludge contains a wide range of contaminants that exhibit differing environmental behaviors. Heavy metals may persist in soils for extended periods and accumulate within agricultural ecosystems. Pathogenic microorganisms can survive under favorable environmental conditions and potentially reach human populations through water and food sources. Pharmaceutical compounds, endocrine-disrupting chemicals, antibiotic-resistant genes, and microplastics present additional concerns because of their persistence, mobility, and potential biological effects (Singh et al., 2018). Environmental conditions such as temperature, rainfall, soil composition, hydrological characteristics, and land-use practices influence the transport and transformation of these contaminants. Consequently, exposure assessment requires analytical methods capable of capturing interactions among numerous environmental variables and quantifying the probability of contaminant movement across ecological systems. Machine learning contributes significantly to the study of environmental exposure pathways by identifying relationships among contaminant sources, environmental conditions, and exposure outcomes (Patil et al., 2021). Predictive models can estimate pollutant transport patterns, classify exposure levels, and evaluate the relative importance of different environmental variables. Spatial analysis techniques supported by machine learning further enhance understanding of geographic variations in exposure risk. Quantitative assessment of environmental pathways provides valuable insights into how sludge-related contaminants interact with ecological systems and influence human populations. Through comprehensive analysis of environmental transport mechanisms and exposure dynamics, researchers can better characterize the complexity of risk distributions within sewerage sludge management systems and strengthen the scientific basis of environmental and public health evaluations (Pérez et al., 2021).

The integration of machine learning and public health analytics represents a significant advancement in the quantitative assessment of risks associated with sewerage sludge management systems. Public health risk analysis traditionally focuses on identifying hazardous agents, evaluating exposure pathways, estimating dose-response relationships, and characterizing potential health outcomes (Xu et al., 2021). Contemporary environmental health research increasingly relies on large and complex datasets derived from epidemiological surveillance systems, environmental monitoring networks, healthcare records, laboratory investigations, and wastewater treatment operations.

Figure 14. Contaminant source–pathway–receptor risk framework for sewerage sludge



The scale and diversity of these datasets necessitate analytical approaches capable of processing extensive information while identifying meaningful patterns that contribute to evidence-based risk assessment. Machine learning techniques provide sophisticated computational tools for analyzing environmental health datasets characterized by high dimensionality, uncertainty, and nonlinear relationships. Algorithms can classify populations according to vulnerability levels, estimate probabilities of exposure, predict contamination events, and identify environmental determinants associated with adverse health outcomes. These capabilities support a more comprehensive understanding of the interactions between environmental contamination and population health (Yousefi et al., 2020). Within sewerage sludge management systems, machine learning models can evaluate relationships among treatment performance, contaminant occurrence, environmental conditions, and public health indicators. Such analyses facilitate the development of quantitative frameworks that capture the complexity of environmental health systems while improving analytical precision and consistency. The application of machine learning to public health risk assessment also supports the integration of environmental, operational, demographic, and epidemiological variables into unified analytical models. This multidimensional perspective enables researchers to investigate how variations in sludge composition, treatment processes, disposal practices, and environmental conditions influence risk outcomes across different populations and geographic settings (Liu et al., 2021). Quantitative machine learning frameworks can process large-scale datasets more efficiently than many traditional analytical methods while maintaining the ability to identify subtle relationships among variables. The resulting insights contribute to a deeper understanding of risk patterns associated with sewerage sludge management systems and provide a scientifically rigorous basis for environmental and public health evaluation. The convergence of environmental science, public health analytics, and machine learning therefore represents a critical development in the quantitative assessment of complex environmental systems where multiple risk factors interact across ecological and human domains (Cicceri et al., 2021).

The primary objective of this quantitative study is to develop and evaluate a machine learning–based framework for assessing environmental and public health risks associated with sewerage sludge management systems through the analysis of multidimensional environmental, operational, and health-related datasets. The study aims to quantitatively examine the relationships between sludge characteristics, contaminant concentrations, treatment processes, disposal practices, and associated risk indicators to generate a comprehensive understanding of how sewerage sludge management influences environmental quality and human health outcomes. Specifically, the research seeks to identify key environmental pollutants, including heavy metals, pathogenic microorganisms, pharmaceutical residues, microplastics, and other emerging contaminants, that contribute to ecological degradation and potential human exposure within sludge management systems. Another objective is to measure the predictive capability of machine learning algorithms in detecting patterns, trends, and risk levels that may not be readily observable through conventional statistical assessment approaches. The study further intends to evaluate the effectiveness of different sludge treatment and disposal methods by analyzing quantitative performance indicators and environmental monitoring data collected from relevant operational settings. In addition, the research aims to classify risk categories and estimate the probability of environmental contamination events and public health hazards using data-driven predictive models. The investigation also seeks to determine the relative influence of operational variables, treatment efficiency parameters, climatic conditions, and contaminant characteristics on overall environmental and health risk outcomes. Through the application of machine learning techniques, the study intends to enhance the accuracy, consistency, and reliability of quantitative risk assessment processes while facilitating the identification of critical factors associated with sludge-related hazards. Furthermore, the research aims to establish an analytical framework capable of integrating large-scale environmental and health datasets to support systematic evaluation of sewerage sludge management systems across diverse contexts. By quantitatively assessing complex interactions among environmental, technological, and health variables, the study seeks to provide a robust empirical foundation for understanding risk distributions and exposure pathways within sewerage sludge management operations, thereby contributing to the advancement of evidence-based environmental risk assessment methodologies.

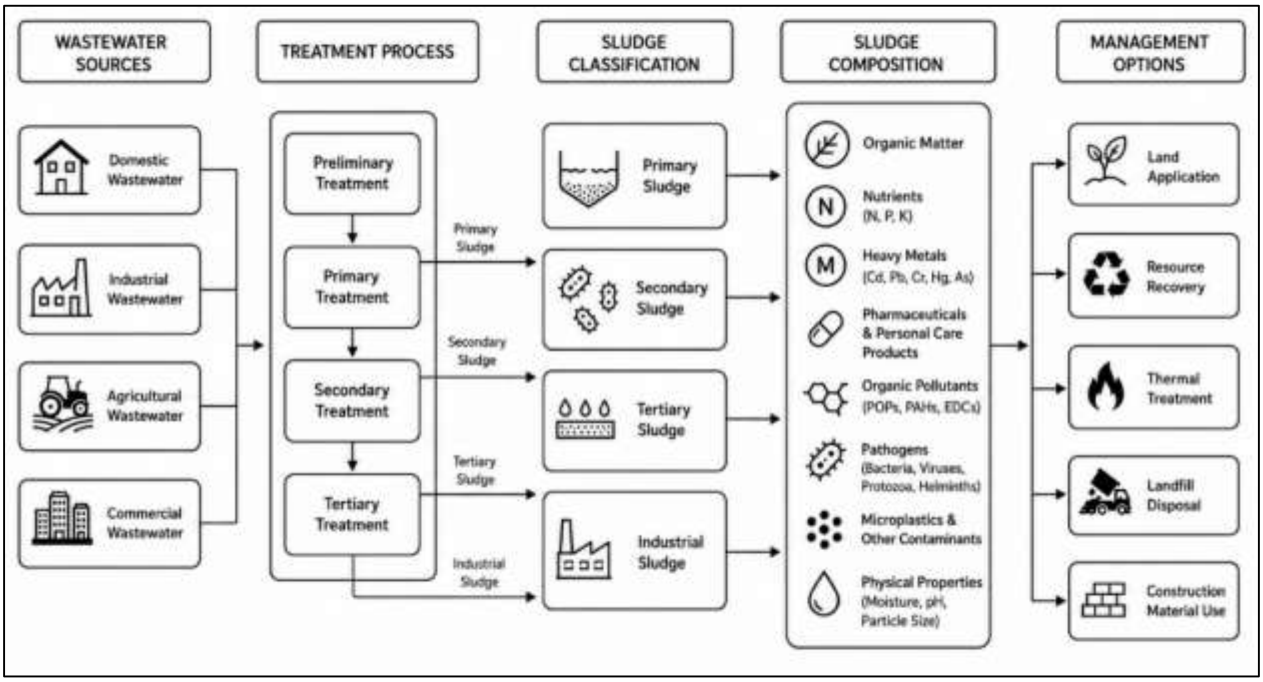
LITERATURE REVIEW

The literature surrounding machine learning–based assessment of environmental and public health risks in sewerage sludge management systems spans multiple interdisciplinary domains, including environmental engineering, wastewater treatment, public health, environmental toxicology, risk assessment, data analytics, artificial intelligence, and computational modeling. Sewerage sludge management has emerged as a critical environmental concern due to the increasing generation of sludge from municipal and industrial wastewater treatment facilities worldwide. The complex composition of sludge, which includes organic matter, nutrients, pathogens, heavy metals, pharmaceutical residues, endocrine-disrupting compounds, antibiotic-resistant genes, and microplastics, creates substantial challenges for environmental monitoring and public health protection (Golam & Amir, 2022; Heo et al., 2021). Consequently, researchers have devoted significant attention to understanding the environmental behavior of sludge contaminants, evaluating treatment technologies, quantifying ecological impacts, and assessing human exposure pathways associated with sludge handling, disposal, and reuse practices. The advancement of quantitative environmental research has expanded the application of predictive analytics and machine learning methodologies within wastewater and sludge management studies. Traditional environmental risk assessment models have historically relied on deterministic approaches, statistical analysis, and laboratory-based investigations. Contemporary research increasingly integrates machine learning algorithms to analyze large environmental datasets, identify complex relationships among variables, improve prediction accuracy, and support evidence-based environmental management decisions (Binayan & Shakhawat, 2022; Sundui et al., 2021). The growing availability of environmental monitoring data, sensor technologies, remote sensing systems, and digital wastewater management platforms has accelerated the adoption of computational approaches capable of handling multidimensional environmental information. Within this context, machine learning has become an important analytical tool for predicting contaminant occurrence, evaluating treatment performance, estimating ecological risks, classifying public health hazards, and identifying key determinants of environmental vulnerability. This literature review synthesizes existing quantitative research on sewerage sludge management, environmental contamination pathways, public health risk assessment frameworks, machine learning applications in environmental systems, predictive modeling techniques, and integrated environmental-health analytics. Particular emphasis is placed on studies that utilize quantitative methodologies to evaluate sludge-related environmental hazards and public health outcomes (Hasan & Uddin, 2022; Yang et al., 2021). The review also examines the evolution of machine learning approaches in wastewater and environmental management, highlighting methodological developments that contribute to more accurate and data-driven risk assessment frameworks. Through a structured examination of the literature, the review establishes the theoretical, methodological, and analytical foundations necessary for investigating machine learning–based assessment of environmental and public health risks within sewerage sludge management systems.

Theoretical Foundations of Sewerage Sludge Management Systems

Sewerage sludge is widely recognized as the residual semi-solid material generated during the treatment of municipal and industrial wastewater. Environmental engineering literature characterizes sludge as a heterogeneous mixture containing organic matter, inorganic compounds, nutrients, microorganisms, suspended solids, trace metals, and a variety of emerging contaminants originating from domestic, commercial, agricultural, and industrial activities. Research has consistently demonstrated that the composition of sludge varies significantly according to wastewater source characteristics, treatment technologies, population density, industrial contributions, and regional environmental conditions (Cheng et al., 2020; Hossain & Uddin, 2022). The increasing complexity of wastewater streams has resulted in sludge matrices that contain both beneficial constituents, such as nitrogen, phosphorus, and organic carbon, and potentially hazardous substances, including heavy metals, pharmaceuticals, endocrine-disrupting compounds, antibiotic residues, and microplastics. Consequently, sludge is increasingly viewed not only as a waste product but also as a resource with environmental, economic, and public health dimensions. Quantitative environmental studies have highlighted the importance of understanding sludge composition because constituent concentrations directly influence treatment efficiency, disposal options, regulatory compliance, and risk assessment outcomes.

Figure 3: Wastewater treatment and sludge management flowchart



The diversity of contaminants identified in modern sludge systems has encouraged extensive scientific investigation into pollutant occurrence, persistence, and mobility across environmental compartments. Within environmental engineering frameworks, sludge characterization serves as a foundational component for evaluating treatment performance and environmental sustainability (Latosińska et al., 2021; Sany & Siful, 2022). Researchers have emphasized that accurate classification and compositional assessment provide critical information for determining suitable management strategies, assessing ecological risks, and supporting resource recovery initiatives. The growing volume of wastewater generated by urbanization and industrial expansion has further intensified interest in sludge

characterization, making it a central topic in environmental engineering and wastewater management research.
The classification of sewerage sludge has evolved considerably as wastewater treatment systems have become more technologically advanced and environmentally regulated (Abdur & Iftekhar, 2021; Przydatek & Wota, 2019). Environmental engineering literature commonly categorizes sludge according to its origin, treatment status, physical characteristics, and intended end-use applications. Primary sludge originates from sedimentation processes where settleable solids are removed from raw wastewater, while secondary sludge results from biological treatment processes involving microbial degradation of organic pollutants. Additional classifications distinguish tertiary sludge generated during advanced treatment operations and industrial sludge produced by manufacturing activities. Researchers have emphasized that classification systems facilitate comparative analysis among treatment facilities and support the development of management protocols tailored to specific sludge characteristics. Quantitative investigations reveal substantial variability in moisture content, volatile solids concentration, nutrient levels, pathogen occurrence, and contaminant profiles across different sludge categories. Such variability influences treatment requirements, transportation costs, disposal feasibility, and environmental performance (Bagherzadeh et al., 2021; Taufiqur & Khalid, 2022). Studies examining sludge classification have demonstrated that treatment stage and source composition significantly affect the chemical and biological properties of residual materials. Environmental regulators frequently incorporate classification criteria into policy frameworks to ensure that sludge management practices align with environmental protection objectives and public health standards. The literature also highlights the importance of standardized classification approaches in facilitating data comparability across jurisdictions and treatment systems. Through systematic categorization, environmental engineers can better assess sludge quality, identify treatment needs, and evaluate potential environmental impacts associated with disposal and reuse activities (Iftekhar & Binayan, 2023; Zeinolabedini & Najafzadeh, 2019).
The compositional complexity of sewerage sludge has become a major focus of quantitative environmental engineering research due to the increasing presence of emerging contaminants in wastewater systems. Contemporary studies indicate that sludge functions as a sink for numerous pollutants that are removed from wastewater during treatment processes. Organic pollutants, pharmaceuticals, personal care products, persistent organic compounds, and microplastics have been detected in varying concentrations across treatment facilities worldwide. Simultaneously, sludge remains an important reservoir of nutrients that contribute to soil fertility and agricultural productivity when appropriately managed (Harrou et al., 2018; Hasan & Chapal, 2023). This dual nature has stimulated extensive investigation into contaminant distribution, nutrient recovery potential, and environmental safety considerations. Quantitative analyses demonstrate that contaminant concentrations often vary according to industrial activities, treatment efficiency, seasonal conditions, and wastewater composition. Researchers have therefore emphasized comprehensive sludge characterization as an essential prerequisite for environmental risk assessment and resource management. Environmental engineering literature increasingly integrates advanced analytical techniques to evaluate sludge composition at both macro and micro scales, enabling more detailed understanding of contaminant behavior and treatment outcomes. These investigations contribute to the development of scientifically informed management practices that address environmental protection requirements while recognizing the potential resource value of treated sludge materials (Mamandipoor et al., 2020; Aminul & Sheak, 2023).
Environmental engineering perspectives increasingly conceptualize sewerage sludge as a dynamic environmental matrix whose characteristics reflect broader socioeconomic, technological, and ecological processes occurring within urban systems. The growth of industrial production, pharmaceutical consumption, chemical manufacturing, and modern consumer lifestyles has significantly influenced the composition of wastewater entering treatment facilities. As a result, sludge composition now serves as an indicator of anthropogenic activities and environmental pressures affecting wastewater infrastructure. Quantitative studies have demonstrated strong relationships between regional economic development and the occurrence of specific contaminants within sludge systems (Nair & Vijaya, 2021; Risha & Khalid, 2023). Researchers have also examined the implications

of sludge composition for circular economy initiatives, sustainable resource management, and environmental quality preservation. The literature emphasizes that understanding the physical, chemical, and biological properties of sludge is fundamental to evaluating treatment performance and environmental risk. Comprehensive characterization enables environmental engineers to identify contamination sources, monitor treatment effectiveness, and assess the suitability of sludge for various disposal or reuse applications. Through these analytical efforts, sewerage sludge has become a critical subject of interdisciplinary research that integrates environmental science, public health, engineering, and sustainability studies (Sany & Uddin, 2023; Strande et al., 2018). This evolving perspective highlights the importance of systematic sludge classification and compositional analysis as foundational elements within quantitative environmental engineering investigations.

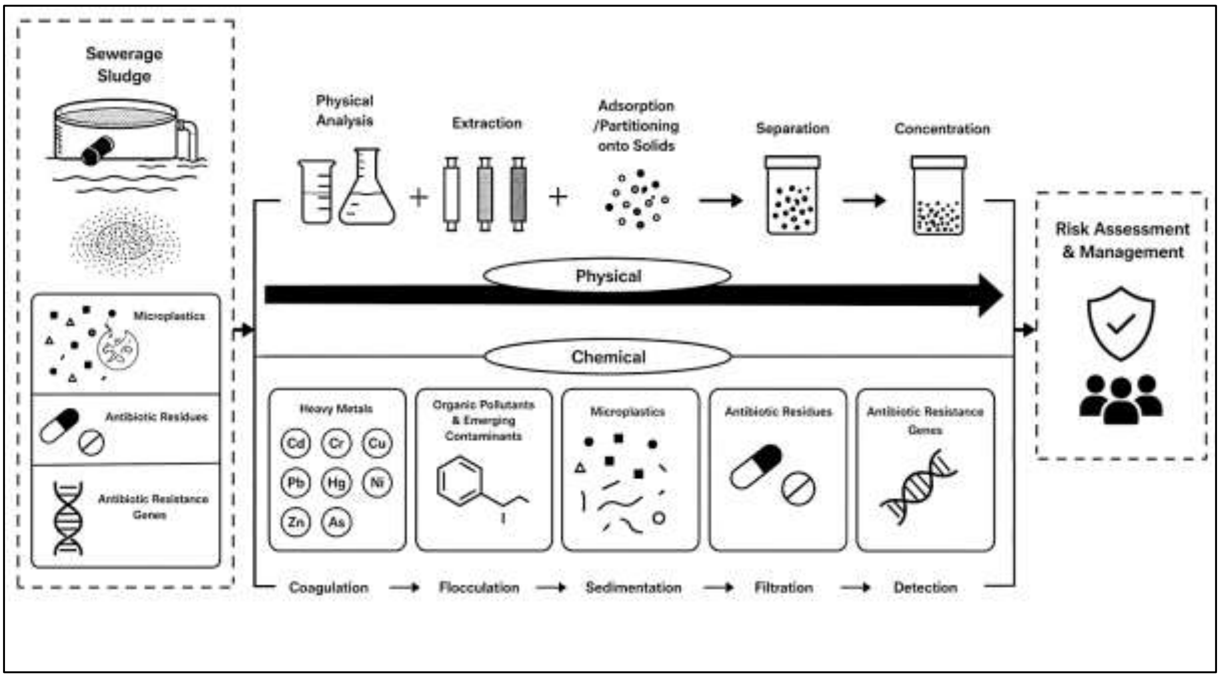
QEnvironmental Contaminants in Sewerage Sludge

Quantitative assessment of heavy metals in sewerage sludge has remained a major focus of environmental contamination research because sludge commonly accumulates metallic elements removed from municipal and industrial wastewater during treatment. The literature identifies cadmium, chromium, copper, lead, mercury, nickel, zinc, and arsenic as among the most frequently analyzed metals in sludge matrices due to their persistence, toxicity, bioaccumulation potential, and relevance to land application standards (Bertanza et al., 2016). Studies show that metal concentrations vary widely across treatment facilities because influent wastewater composition is shaped by industrial activity, household discharge, urban runoff, treatment design, and regional regulation. Quantitative investigations commonly evaluate total concentration, chemical fractionation, mobility, and potential ecological risk in order to determine whether sludge is suitable for agricultural use, landfill disposal, composting, or thermal treatment. Heavy metals are particularly important because they do not degrade biologically and may remain in soils for long periods after sludge application. Their persistence increases concerns about crop uptake, groundwater contamination, and long-term ecological exposure. Comparative studies also indicate that sludge treatment processes may reduce pathogen loads and organic matter instability while having limited ability to eliminate metals completely (Abdallah et al., 2020). Therefore, the quantitative measurement of heavy metal occurrence provides a critical foundation for evaluating the environmental safety of sludge reuse and disposal systems. Research further demonstrates that risk is not determined by concentration alone, since metal speciation, soil pH, organic matter, cation exchange capacity, and land-use conditions influence mobility and bioavailability. As a result, literature-based assessment increasingly combines concentration data with ecological risk indices and contamination factors to generate more complete evaluations of heavy metal hazards in sludge management systems.

The quantitative measurement of organic pollutants and emerging contaminants in sewerage sludge has expanded significantly as wastewater treatment plants have become recognized as collection points for complex chemical residues generated by modern society (Ahmad et al., 2017). Literature on sludge contamination reports the frequent occurrence of persistent organic pollutants, polycyclic aromatic hydrocarbons, flame retardants, surfactants, endocrine-disrupting compounds, pesticides, pharmaceuticals, and personal care products. These contaminants enter wastewater streams through domestic consumption, hospital discharge, industrial production, agricultural runoff, and urban chemical use. During treatment, many hydrophobic and semi-persistent substances partition into sludge because of their affinity for organic matter and suspended solids. Quantitative studies often focus on concentration distribution, removal behavior, persistence, degradation potential, and accumulation across treatment stages. Pharmaceutical and personal care products receive particular attention because antibiotics, analgesics, hormones, antimicrobials, and cosmetic-related compounds may remain detectable in treated sludge. Their presence raises environmental concerns because land-applied sludge can transfer residues into soils, drainage systems, and biological communities (Grönlund, 2019). The literature shows that contaminant levels differ according to treatment technology, sludge age, digestion conditions, temperature, and local consumption patterns. Anaerobic digestion, composting, lime stabilization, and thermal treatment may reduce some organic contaminants, although removal efficiency varies widely by compound class. Quantitative investigations therefore emphasize the need to evaluate sludge as a chemically diverse matrix rather than a uniform waste material. Emerging contaminants are especially relevant to machine learning–

based risk assessment because their behavior is shaped by multiple interacting variables, making predictive analytics useful for identifying contamination patterns and estimating risk levels across treatment systems (Fijalkowski et al., 2017). Recent sludge contamination literature has placed increasing emphasis on microplastics, antibiotic residues, and antibiotic resistance genes because these contaminants represent complex environmental and public health concerns.

Figure 4: Sludge contaminants flowchart diagram



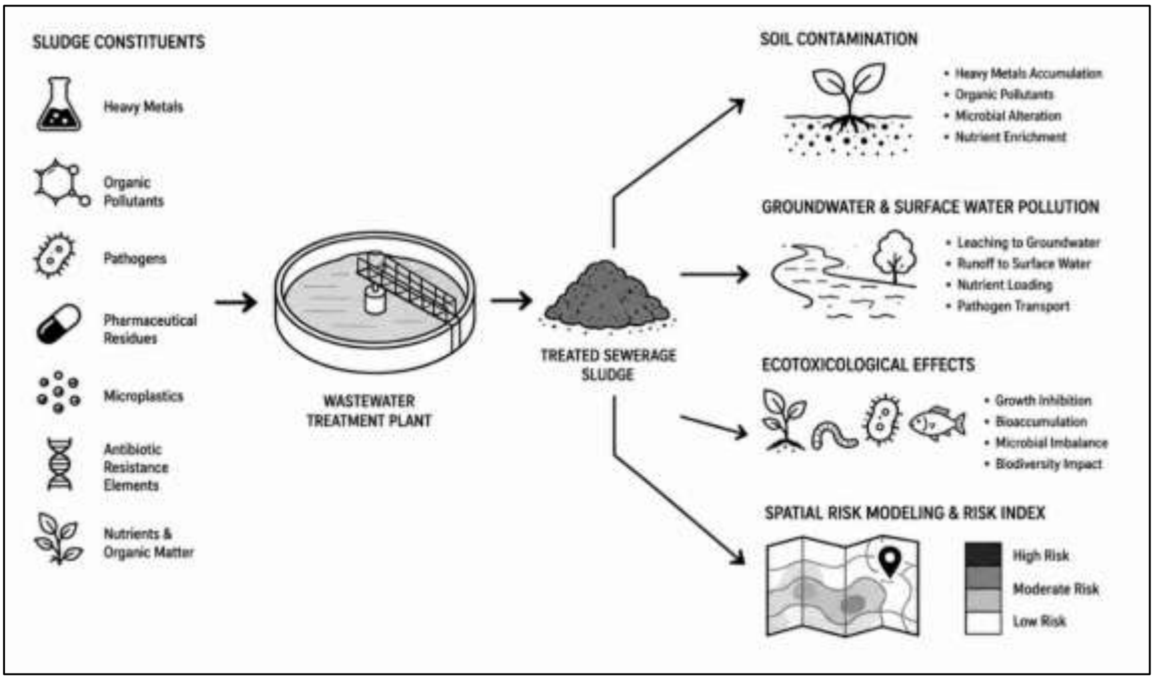
Sewerage sludge is widely reported as a sink for microplastics originating from synthetic textiles, personal care products, packaging materials, tire particles, and urban wastewater inputs. Quantitative studies have measured microplastic abundance, particle size, polymer type, morphology, and distribution across sludge treatment stages. Fibers, fragments, films, and beads are frequently detected, with concentrations varying according to wastewater source, sampling method, analytical technique, and treatment efficiency. The environmental mobility of microplastics becomes important when sludge is applied to land, as particles may accumulate in soils, alter soil structure, interact with microorganisms, and transport adsorbed pollutants (Latosińska et al., 2021). Alongside microplastics, antibiotic residues and resistance genes have become key indicators of biological and chemical risk in sludge systems. Wastewater treatment environments can concentrate antibiotics, resistant bacteria, and genetic elements associated with resistance transmission. Quantitative research has documented the occurrence of resistance genes linked to tetracyclines, sulfonamides, macrolides, beta-lactams, and other antibiotic classes in sludge samples. These findings are significant because sludge treatment may reduce microbial loads while leaving detectable genetic residues or resistant microbial communities. Statistical analysis of antibiotic residues and resistance genes often examines correlations among antibiotic concentration, microbial diversity, treatment process, and environmental persistence. Literature also indicates that composting, anaerobic digestion, thermal hydrolysis, and advanced stabilization can reduce some resistance indicators, although performance varies (Rorat et al., 2019). This body of research supports the view that sludge contaminant assessment must include both chemical and biological risk markers to capture the full range of environmental and public health hazards.

Ecological Risk Modeling in Sludge Management Systems

Soil contamination following sewerage sludge application has been widely examined in environmental literature because land application remains one of the most common sludge management practices in many regions. Treated sludge contains organic matter and nutrients that may improve soil structure, microbial activity, and fertility; however, it can also introduce heavy metals, persistent organic compounds, pathogens, pharmaceutical residues, microplastics, and antibiotic resistance elements into agricultural and non-agricultural soils. Quantitative studies have shown that contaminant behavior in soil depends on sludge composition, application rate, treatment quality, soil pH, organic matter content, clay fraction, rainfall intensity, crop type, and land management practices (Tytła, 2019). Heavy metals such as cadmium, lead, nickel, chromium, copper, zinc, and mercury receive particular attention because they persist in soil and may accumulate after repeated sludge application. Organic pollutants and emerging contaminants also interact with soil particles and microbial communities, influencing degradation, retention, and mobility. Literature further indicates that sludge-derived contaminants may alter soil enzymatic activity, microbial diversity, nutrient cycling, and plant uptake patterns. These findings position soil as a central environmental receptor in sludge-related risk assessment. Ecological risk modeling in this context often evaluates contamination levels, accumulation patterns, mobility potential, and toxicity indicators to determine whether sludge-amended soils remain within acceptable environmental quality standards (Nakic, 2018). The literature therefore presents soil contamination dynamics as a key pathway through which sewerage sludge management can influence terrestrial ecosystems, agricultural productivity, and indirect human exposure through food chain transfer.

Groundwater and surface water pollution risk assessment has become an important part of sludge management research because contaminants released from sludge-amended soils can move through runoff, infiltration, erosion, drainage, and leaching processes. Quantitative environmental studies show that nutrients, pathogens, heavy metals, dissolved organic compounds, pharmaceutical residues, and antibiotic resistance genes may enter aquatic systems when sludge is applied under unsuitable soil, slope, rainfall, or hydrological conditions. Groundwater vulnerability is strongly influenced by soil permeability, water table depth, contaminant solubility, rainfall frequency, and the chemical properties of sludge-derived pollutants. Surface water contamination is commonly associated with stormwater runoff, erosion of treated land, and transport of contaminated soil particles into rivers, lakes, canals, and reservoirs (Buonocore et al., 2018).

Figure 5: Wastewater treatment and environmental risks



Research on contaminant leaching emphasizes that pollutants do not move uniformly through environmental systems; instead, their transport depends on sorption behavior, degradation rate, soil chemistry, and hydrological connectivity. Nitrogen and phosphorus are frequently studied because excessive loading may contribute to eutrophication and water quality deterioration. Pathogens and antibiotic resistance markers are also important because aquatic transport may extend public health exposure beyond the original sludge application site. Environmental modeling studies have therefore used quantitative indicators to estimate pollutant mobility, identify vulnerable water bodies, and classify pollution risk levels. This literature shows that water-related exposure pathways connect sludge management practices with broader ecological and public health concerns, especially in areas with intensive land application, weak monitoring systems, or sensitive hydrological environments (Mailler et al., 2017).

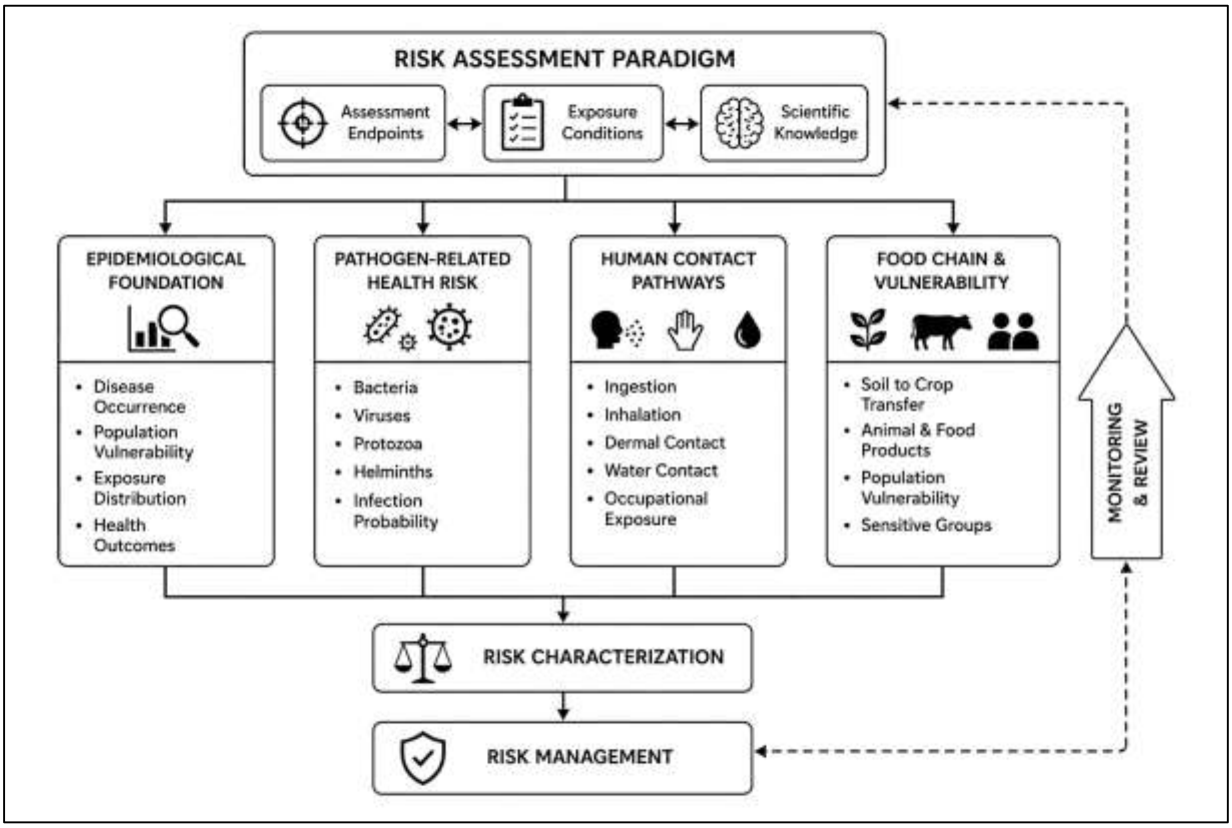
Ecotoxicological assessment of sludge-derived pollutants provides a scientific basis for understanding how contaminants affect organisms, biological communities, and ecosystem functions. Research in this area examines the effects of sludge-associated heavy metals, organic contaminants, pharmaceuticals, endocrine-disrupting compounds, microplastics, pathogens, and antibiotic resistance elements on plants, soil organisms, aquatic species, and microbial communities. Quantitative ecotoxicological studies commonly evaluate toxicity responses, bioaccumulation, growth inhibition, reproductive disruption, microbial imbalance, oxidative stress, and changes in biodiversity indicators. Earthworms, soil microorganisms, algae, aquatic invertebrates, and crop plants are frequently used as biological indicators because they respond to contaminant exposure in measurable ways (Nkinahamira et al., 2019). The literature shows that ecological risk is shaped not only by the presence of individual contaminants but also by combined exposure to multiple pollutants in complex sludge matrices. Mixed contaminant effects are especially relevant because sludge may contain metals, organic chemicals, nutrients, and biological hazards simultaneously. Studies have also emphasized that contaminant bioavailability often determines ecological harm more accurately than total concentration alone. Factors such as soil pH, organic matter, temperature, moisture, and microbial activity influence whether contaminants remain immobilized or become available to organisms. Ecotoxicological findings therefore strengthen environmental risk models by linking chemical measurements with biological responses. Within sludge management systems, this evidence supports a more integrated understanding of environmental exposure, where contaminant persistence, transport, and toxicity are analyzed together to assess ecological risk across terrestrial and aquatic environments (Tarpani et al., 2020).

Spatial distribution modeling and environmental risk index development have become central approaches in the assessment of sludge-related exposure pathways because contamination risks are rarely distributed evenly across landscapes. Literature shows that environmental risk hotspots often occur near wastewater treatment facilities, sludge storage areas, land application sites, agricultural fields, drainage channels, and downstream aquatic environments. Geographic information systems, statistical mapping, and spatial modeling techniques are frequently used to identify areas with elevated contaminant concentrations, vulnerable soil conditions, dense populations, or sensitive ecosystems. Quantitative hotspot analysis helps researchers examine how land use, topography, hydrology, climate, treatment practices, and disposal intensity influence the spatial pattern of environmental risk. Risk indices are also widely used to combine multiple contamination indicators into interpretable categories of low, moderate, high, or severe risk (Raheem et al., 2018). These indices often incorporate contaminant concentration, toxicity, background levels, ecological sensitivity, and exposure potential. Validation is an essential part of risk index development because models must demonstrate consistency, reliability, and relevance across different locations and datasets. Comparative studies indicate that validated risk models provide stronger evidence for assessing sludge management performance than isolated measurements of individual contaminants. The literature also highlights that spatial and index-based approaches are useful for comparing treatment systems, identifying priority monitoring areas, and interpreting complex contaminant profiles. In sewerage sludge management research, these quantitative tools create a structured basis for linking contaminant sources, exposure pathways, ecological vulnerability, and observed environmental outcomes within a measurable risk assessment framework (Bondarczuk et al., 2016).

Risk Assessment Frameworks for Sewerage Sludge Exposure

Public health risk assessment for sewerage sludge exposure is grounded in epidemiological approaches that examine how environmental hazards influence disease occurrence, population vulnerability, and exposure distribution. Sewerage sludge may contain pathogenic microorganisms, toxic metals, pharmaceutical residues, endocrine-disrupting compounds, antibiotic-resistant bacteria, and persistent organic pollutants that can enter human environments through soil, water, air, occupational contact, and food systems. Epidemiological literature frames sludge-related risk as a relationship between hazard presence, exposure intensity, exposure duration, population susceptibility, and measurable health outcomes (Bondarczuk et al., 2016). Within this framework, public health assessment does not focus only on the chemical or biological properties of sludge but also on the conditions under which people encounter sludge-derived contaminants. Communities located near wastewater treatment plants, agricultural lands receiving biosolids, sludge storage sites, and disposal facilities may experience different levels of environmental exposure depending on local sanitation systems, land-use patterns, hydrological conditions, and regulatory control. Quantitative environmental health studies commonly assess associations between contaminant occurrence and outcomes such as gastrointestinal illness, respiratory symptoms, skin irritation, parasitic infection, microbial exposure, and long-term toxicological effects. This literature shows that sludge exposure assessment requires integration of environmental monitoring, health surveillance, microbial testing, and exposure pathway analysis. Epidemiological foundations are therefore essential because they connect environmental contamination data with human health evidence, allowing sewerage sludge management to be evaluated as both an environmental engineering issue and a population health concern (Yakamercan et al., 2021).

Figure 6: Risk assessment paradigm flowchart



Pathogen-related health risk assessment is one of the most important components of sewerage sludge exposure research because untreated or insufficiently treated sludge may contain bacteria, viruses, protozoa, helminths, and other infectious agents. Quantitative studies have examined the survival, reduction, regrowth, and environmental transport of pathogens during sludge treatment, storage, land application, and disposal. Pathogens commonly investigated in sludge-related research include fecal coliforms, Salmonella, Escherichia coli, enteric viruses, Giardia, Cryptosporidium, and helminth eggs. Their presence is significant because exposure may occur through direct handling, aerosol inhalation, contaminated crops, polluted water, or accidental contact with sludge-amended soils. The literature shows that pathogen risk depends on treatment method, temperature, moisture, retention time, sludge stabilization quality, application practices, and environmental conditions after disposal. Anaerobic digestion, composting, lime treatment, drying, and thermal processes can reduce pathogen loads, although effectiveness varies according to operational control and microbial resistance (Duan et al., 2017). Quantitative microbial risk assessment has been widely used to estimate infection probability by combining information on pathogen concentration, exposure frequency, dose-response relationships, and population susceptibility. These approaches help determine whether sludge treatment processes achieve acceptable health protection levels. Public health studies also emphasize that pathogen-related risks are especially relevant for workers, farmers, nearby residents, children, and immunocompromised individuals. As a result, pathogen quantification has become a central indicator in assessing the safety of sludge management systems and their potential contribution to communicable disease risks.

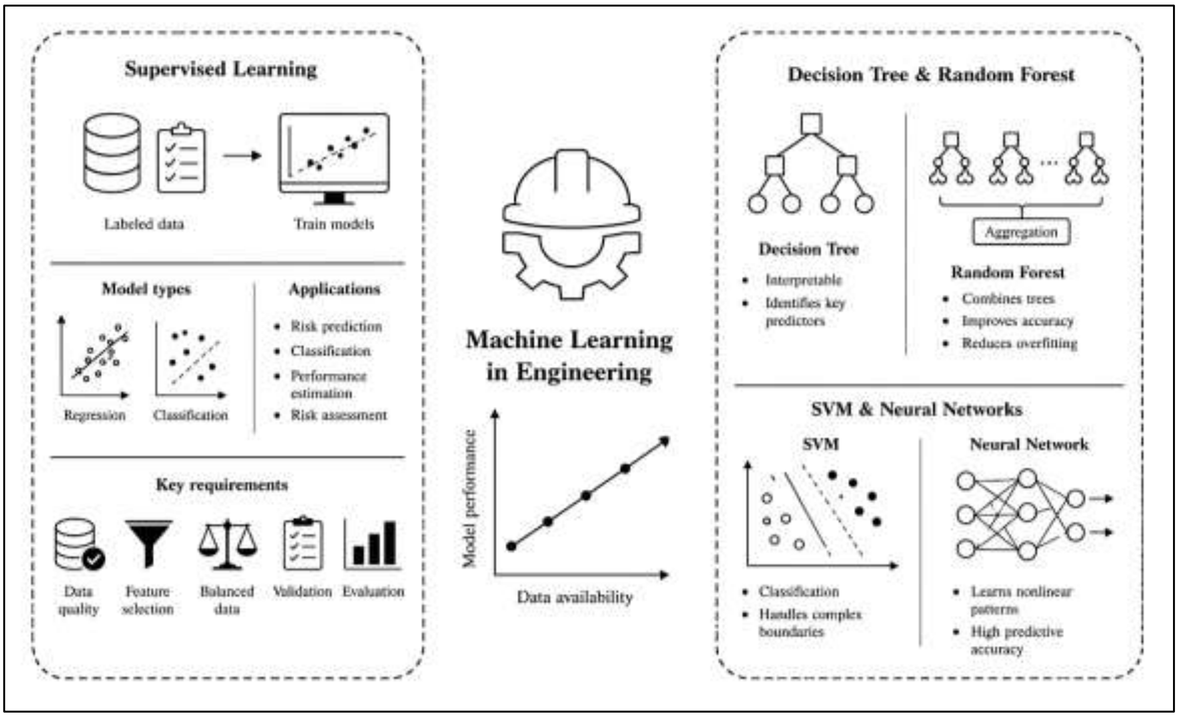
Exposure assessment models for sludge-associated human contact pathways provide a structured basis for understanding how contaminants move from sludge systems to individuals and occupational groups (Harder et al., 2016). Human exposure may occur through ingestion of contaminated soil or food, inhalation of bioaerosols and dust, dermal contact during handling, consumption of contaminated water, or contact with polluted environmental surfaces. Occupational exposure is particularly important because workers involved in wastewater treatment, sludge dewatering, transportation, composting, land application, and disposal may experience repeated contact with biological and chemical hazards. Literature on occupational health in sludge handling operations identifies risks related to microbial aerosols, endotoxins, volatile compounds, heavy metals, sharp materials, and unpleasant odors that may affect respiratory, gastrointestinal, dermatological, and general health outcomes. Statistical studies of workplace exposure often examine symptom prevalence, microbial concentrations, air quality indicators, protective equipment use, and task-specific exposure levels. The evidence indicates that exposure intensity varies by job role, facility design, ventilation conditions, sludge treatment stage, handling method, and worker safety practices. Exposure models therefore help quantify differences between direct and indirect contact, short-term and repeated exposure, and occupational and community-level risk (Mills et al., 2018). These models also allow researchers to compare measured contaminant levels with health-based benchmarks. In public health risk assessment, human contact pathway analysis strengthens the interpretation of environmental monitoring data by showing how contaminants become biologically relevant to exposed populations. This perspective is essential for evaluating sewerage sludge management systems from a health protection standpoint.

Food chain–mediated exposure is a major concern in sludge management because treated sludge is often applied to agricultural land as a source of nutrients and organic matter. Literature shows that contaminants present in sludge-amended soils may be transferred to crops, grazing animals, surface water, and food products through plant uptake, soil ingestion by livestock, irrigation pathways, and ecological accumulation (Daley et al., 2018). Heavy metals such as cadmium, lead, mercury, and arsenic are frequently studied because they may persist in soils and enter edible plant tissues under specific soil and crop conditions. Organic contaminants, pharmaceutical residues, microplastics, and antibiotic resistance elements also raise concern because their movement through food systems remains complex and variable. Quantitative investigation of food chain exposure commonly evaluates contaminant concentration in soil, crop tissues, irrigation water, animal products, and human dietary intake estimates. Public health vulnerability assessment extends this analysis by considering population characteristics such as age, immune status, occupation, diet, proximity to sludge application sites, sanitation access, and socioeconomic conditions. Environmental monitoring data are used to identify groups with higher exposure potential and to classify risk across geographic areas. The literature emphasizes that vulnerability is not determined by contaminant concentration alone; it is shaped by the interaction of environmental conditions, agricultural practices, treatment quality, consumption patterns, and community health status (Amoah, et al., 2020). Therefore, public health risk assessment frameworks for sewerage sludge exposure require integrated quantitative analysis of environmental contamination, human behavior, food pathways, and population sensitivity.

Machine Learning Algorithms for Environmental Risk Prediction

Supervised learning has become a central methodological foundation in quantitative environmental analytics because it enables researchers to train predictive models using labeled environmental datasets where input variables are linked to known outcomes. In environmental risk prediction, these outcomes may include contamination levels, risk categories, treatment performance classes, pollutant exceedance status, pathogen presence, or ecological hazard scores. Literature on environmental data science shows that supervised learning is particularly useful when large volumes of historical monitoring data are available from wastewater treatment plants, soil testing programs, water quality assessments, sludge characterization studies, and public health surveillance systems (Gil-Solsona et al., 2021). These datasets often include chemical, biological, operational, climatic, and spatial variables that interact in complex ways. Traditional statistical techniques remain useful for hypothesis testing and linear association analysis, while supervised machine learning provides stronger flexibility for detecting nonlinear relationships, hidden patterns, and multidimensional interactions. In sewerage sludge management, supervised learning can support classification of sludge quality, prediction of contaminant concentration groups, estimation of treatment efficiency, and identification of environmental risk levels. Regression-based machine learning models are commonly applied when the outcome is continuous, such as heavy metal concentration or organic pollutant load, whereas classification models are used when the objective is to categorize observations into risk groups. The literature emphasizes that supervised learning performance depends heavily on data quality, feature selection, balanced datasets, model validation, and appropriate evaluation metrics (Lane et al., 2021). Therefore, supervised learning provides a quantitative foundation for transforming environmental monitoring records into predictive evidence for sludge-related risk assessment.

Figure 7: Machine learning methods in engineering



Decision tree and random forest models are widely discussed in environmental risk prediction literature because they offer interpretable and flexible approaches for classifying complex environmental data. Decision trees divide data into branches based on variable thresholds, making them useful for identifying key predictors of risk in sludge treatment and contamination studies. Their structure allows researchers to trace how variables such as sludge moisture content, heavy metal concentration, treatment type, pH, organic matter, pathogen level, and disposal method contribute to risk classification (Zhong et al., 2021). However, individual decision trees may be sensitive to data variation, which has encouraged greater use of random forest models . Random forests combine multiple decision trees to improve predictive stability, reduce overfitting, and enhance classification accuracy. In environmental datasets, random forests have been applied to water quality prediction, soil contamination mapping, air pollution classification, wastewater treatment monitoring, and ecological risk assessment. Their strength lies in handling large numbers of predictors, ranking variable importance, and modeling nonlinear interactions without requiring strict distributional assumptions. For sewerage sludge management, random forest models can help identify which contaminants or operational parameters most strongly influence environmental and public health risk levels. Literature also shows that tree-based models perform well when datasets contain mixed variable types, missing values, or complex relationships among predictors (Bellinger et al., 2017). These characteristics make decision trees and random forests valuable for quantitative sludge risk assessment, particularly when the goal is to classify risk categories, detect high-risk samples, and explain the relative contribution of environmental variables.

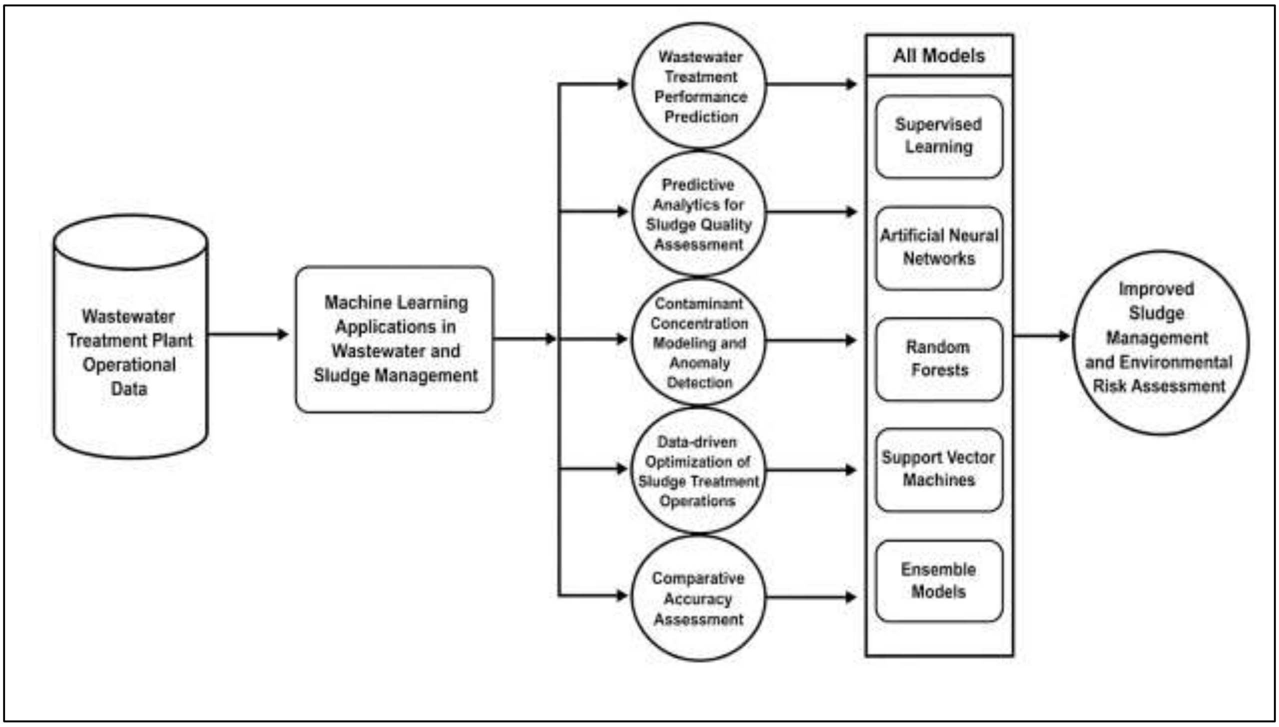
Support vector machines and artificial neural networks have been extensively examined in environmental modeling because they are capable of analyzing complex nonlinear relationships between environmental predictors and risk outcomes. Support vector machines are commonly used for classification and regression problems where the objective is to separate environmental observations into distinct categories or estimate continuous contamination indicators. Their ability to perform well with high-dimensional datasets makes them relevant for environmental hazard detection, especially when sludge datasets include multiple chemical, biological, and operational variables (Mojaddadi et al., 2017). In pollution modeling, support vector machines have been used to predict water quality status, classify contamination severity, estimate pollutant concentration, and detect abnormal environmental conditions. Artificial neural networks, including deeper learning architectures, are also widely used because they can learn layered patterns from complex datasets. These models are especially suitable for pollution systems where relationships among variables are nonlinear, time-dependent, and influenced by multiple interacting factors. In sludge management contexts, neural networks may support prediction of treatment performance, contaminant persistence, pathogen reduction, and environmental exposure potential (Li et al., 2019). Literature indicates that neural network models often achieve strong predictive accuracy when sufficient training data are available, although their interpretability may be lower than tree-based methods. Deep learning approaches have also been applied to sensor-based monitoring, remote sensing data, image-based environmental detection, and high-frequency pollution forecasting. Together, support vector machines and neural networks provide powerful methodological options for quantitative environmental risk prediction where contaminant behavior is complex and conventional linear models may be insufficient (Tonini et al., 2020).

Machine Learning in Wastewater and Sludge Management Systems

Machine learning applications in wastewater treatment performance prediction have become central in quantitative environmental engineering because treatment plants generate large operational datasets that describe influent quality, effluent quality, biological activity, chemical dosing, hydraulic loading, sludge production, aeration performance, and process stability. Literature shows that predictive models are frequently used to estimate key wastewater treatment indicators, including biochemical oxygen demand, chemical oxygen demand, suspended solids, nitrogen, phosphorus, turbidity, dissolved oxygen, and microbial removal efficiency (Sundui et al., 2021). These variables are important because they reflect the operational capacity of treatment systems to reduce pollution before residual sludge is generated. Machine learning models are useful in this context because wastewater treatment processes are nonlinear, variable, and influenced by many interacting environmental and operational factors. Supervised learning, artificial neural networks, random forests, support vector machines, and ensemble models have been applied to predict treatment outcomes more accurately than many conventional linear approaches. In sludge management research, these predictive methods help explain how upstream wastewater treatment conditions influence sludge quantity, sludge composition, contaminant concentration, and stabilization requirements. Quantitative studies also indicate that machine learning can improve interpretation of time-series monitoring data by identifying process shifts, pollutant loading changes, and treatment performance deviations (Miao et al., 2021). This body of literature positions machine learning as a strong analytical tool for connecting wastewater treatment performance with downstream sludge quality and environmental risk assessment.

Predictive analytics for sludge quality assessment focuses on estimating the physical, chemical, and biological characteristics of sludge using environmental monitoring data and operational process indicators. Sludge quality is commonly evaluated through moisture content, volatile solids, nutrient levels, pathogen indicators, heavy metal concentrations, organic contaminant residues, stability, dewaterability, and suitability for disposal or reuse. Literature shows that these characteristics vary according to influent wastewater composition, biological treatment efficiency, sludge age, digestion conditions, temperature, pH, industrial discharge, and treatment technology (Kim & Oh, 2021). Machine learning models have been used to identify relationships among these variables and to classify sludge according to quality levels or management suitability. Predictive models are particularly valuable because laboratory testing may be costly, time-consuming, and periodic, while plant operation data may be available continuously. By analyzing historical relationships between process variables and measured sludge properties, machine learning can support quantitative monitoring of sludge quality under changing operational conditions. Studies also demonstrate that data-driven models can assist in identifying key predictors of sludge stabilization, contaminant retention, and biological activity. Within environmental risk assessment, sludge quality prediction provides a foundation for estimating potential hazards before land application, incineration, composting, anaerobic digestion, or landfill disposal (Wang et al., 2021). Therefore, the literature emphasizes predictive analytics as a methodological bridge between treatment plant monitoring and sludge-related environmental risk evaluation.

Figure 8: Machine learning pipeline for sludge management



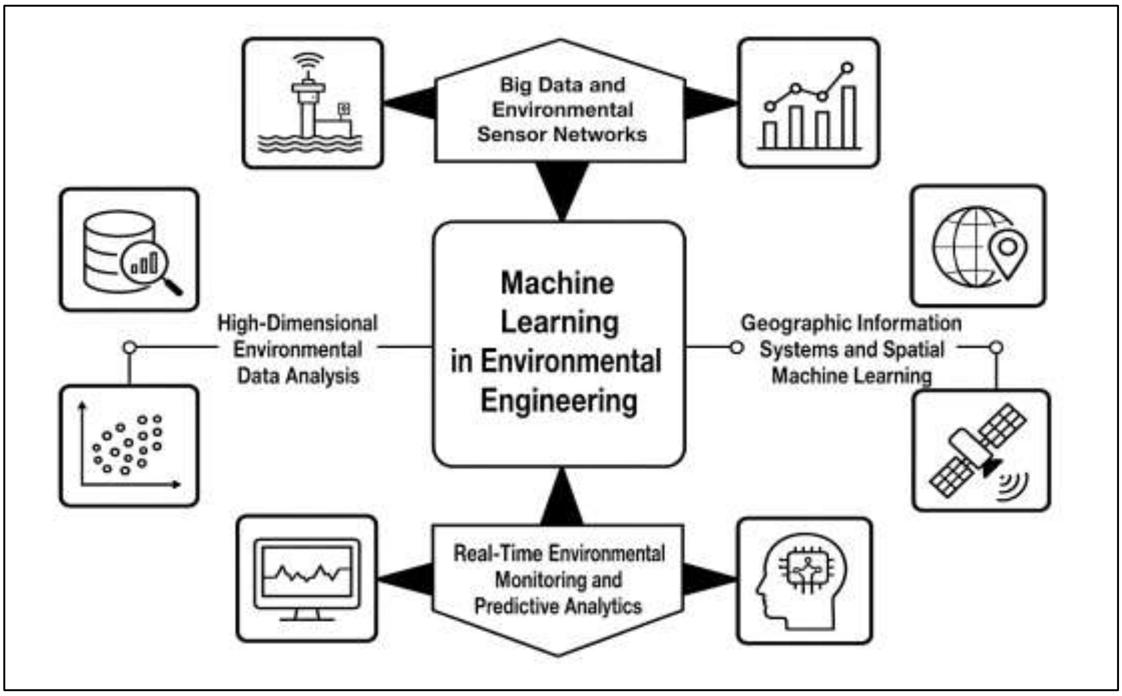
Quantitative modeling of contaminant concentration dynamics is a major application of machine learning in wastewater and sludge management because contaminants fluctuate across treatment stages and environmental conditions. Heavy metals, pharmaceutical residues, organic pollutants, microplastics, nutrients, pathogens, and antibiotic resistance indicators may enter treatment systems at variable concentrations depending on domestic behavior, industrial discharge, hospital waste, rainfall, seasonal changes, and treatment efficiency. Machine learning methods can analyze these complex data patterns and estimate contaminant levels across influent wastewater, activated sludge, digested sludge, biosolids, and final effluent (Hernández-del-Olmo et al., 2019). Literature shows that models such as random forests, neural networks, support vector machines, gradient boosting, and hybrid approaches can capture nonlinear relationships between operational variables and contaminant outcomes. Another important application involves anomaly detection, where algorithms identify unusual process behavior, sudden pollutant loading, sensor irregularities, equipment malfunction, or abnormal sludge characteristics. In wastewater treatment plants, anomalies may indicate hydraulic shock, toxic influent events, aeration imbalance, microbial inhibition, digester instability, or unexpected contaminant accumulation. Machine learning–based anomaly detection strengthens quantitative risk assessment by helping identify patterns that may increase environmental or public health hazards. The literature therefore highlights that contaminant modeling and anomaly detection are closely linked because both depend on recognizing deviations from expected process behavior (Gencosman & Sanli, 2021). These approaches improve understanding of how sludge-related risks emerge within dynamic treatment systems.

Data-driven optimization of sludge treatment operations has been widely discussed in machine learning literature because sludge management involves multiple performance objectives, including contaminant reduction, pathogen control, energy efficiency, cost reduction, resource recovery, odor control, and disposal safety. Machine learning models can support operational optimization by identifying the variables most strongly associated with treatment performance and by comparing alternative process conditions. In sludge treatment, these variables may include retention time, temperature, aeration rate, chemical dosage, solids concentration, digestion stability, moisture content, and dewatering efficiency. Quantitative studies show that machine learning can improve process understanding by ranking predictor importance, detecting operational inefficiencies, and estimating treatment outcomes under different conditions (Newhart et al., 2020). Comparative accuracy assessment is essential because different algorithms perform differently depending on dataset size, variable type, noise level, missing data, and modeling objective. Conventional statistical approaches are often valued for interpretability and hypothesis testing, while machine learning approaches are frequently valued for predictive strength, flexibility, and capacity to model nonlinear interactions. Literature comparing conventional and machine learning methods often evaluates models using accuracy, prediction error, classification performance, validation results, and generalizability across datasets. In wastewater and sludge management systems, these comparisons help determine whether machine learning provides measurable improvement over traditional modeling for contaminant prediction, process monitoring, anomaly detection, and risk classification (Cangialosi et al., 2021). Overall, the literature presents machine learning as a quantitative approach that strengthens sludge management analysis when supported by reliable datasets, appropriate validation procedures, and careful interpretation of model performance.

Big Data and Predictive Analytics in Sludge Management

The emergence of big data in environmental engineering has transformed the monitoring and management of wastewater and sewerage sludge systems by enabling continuous collection of large volumes of environmental information from multiple sources. Environmental sensor networks have become essential components of modern wastewater treatment infrastructure because they provide real-time measurements of physical, chemical, biological, and operational parameters. Sensors are commonly deployed to monitor variables such as pH, dissolved oxygen, temperature, conductivity, turbidity, nutrient concentrations, sludge characteristics, flow rates, and contaminant levels (Cangialosi et al., 2021). The literature indicates that advances in sensor technology have significantly improved the frequency, accuracy, and spatial coverage of environmental data collection. These developments have generated extensive datasets that support quantitative analysis of wastewater treatment performance, sludge quality assessment, contaminant occurrence, and environmental risk evaluation. Data acquisition technologies also include automated monitoring platforms, supervisory control systems, laboratory information management systems, internet-connected devices, and digital environmental reporting frameworks. Together, these technologies create integrated information environments capable of capturing operational changes and environmental conditions at high temporal resolution (Szeląg et al., 2020). Research emphasizes that the increasing availability of sensor-generated information has expanded opportunities for data-driven environmental management while also creating challenges associated with data quality, storage, integration, and interpretation. In sludge management systems, continuous monitoring supports early identification of treatment inefficiencies, contaminant fluctuations, and operational anomalies. Consequently, environmental sensor networks serve as foundational components of modern predictive analytics frameworks by providing the large-scale datasets necessary for quantitative environmental assessment and machine learning applications. The rapid growth of environmental monitoring programs has resulted in the generation of high-dimensional datasets characterized by large numbers of variables, extensive temporal records, and complex interactions among environmental indicators. In wastewater and sludge management systems, datasets frequently include chemical measurements, biological indicators, treatment process variables, climatic conditions, operational records, contaminant profiles, and spatial information (Arismendy et al., 2020). The literature highlights that traditional analytical approaches often encounter limitations when attempting to interpret highly complex datasets containing hundreds or thousands of interconnected observations. Quantitative analysis of high-dimensional environmental data therefore relies increasingly on advanced computational techniques capable of identifying patterns, correlations, clusters, and predictive relationships.Feature selection and dimensionality reduction techniques have become particularly important because they help identify the most relevant predictors while reducing redundancy and computational complexity.

Figure 9: Machine learning in environmental engineering diagram



These methods improve model efficiency by retaining essential information and eliminating variables that contribute little to predictive performance. Studies have demonstrated that environmental datasets often contain substantial noise, multicollinearity, and missing observations, making data preprocessing a critical step in predictive modeling (Ward et al., 2021). Researchers also emphasize the importance of data normalization, feature engineering, and variable selection for improving model accuracy and interpretability. Within sludge management research, quantitative analysis of high-dimensional datasets facilitates improved understanding of contaminant behavior, treatment system performance, environmental exposure pathways, and public health risk indicators. The literature therefore presents advanced data analytics as a necessary component of modern environmental management because it enables meaningful interpretation of increasingly complex environmental information systems.

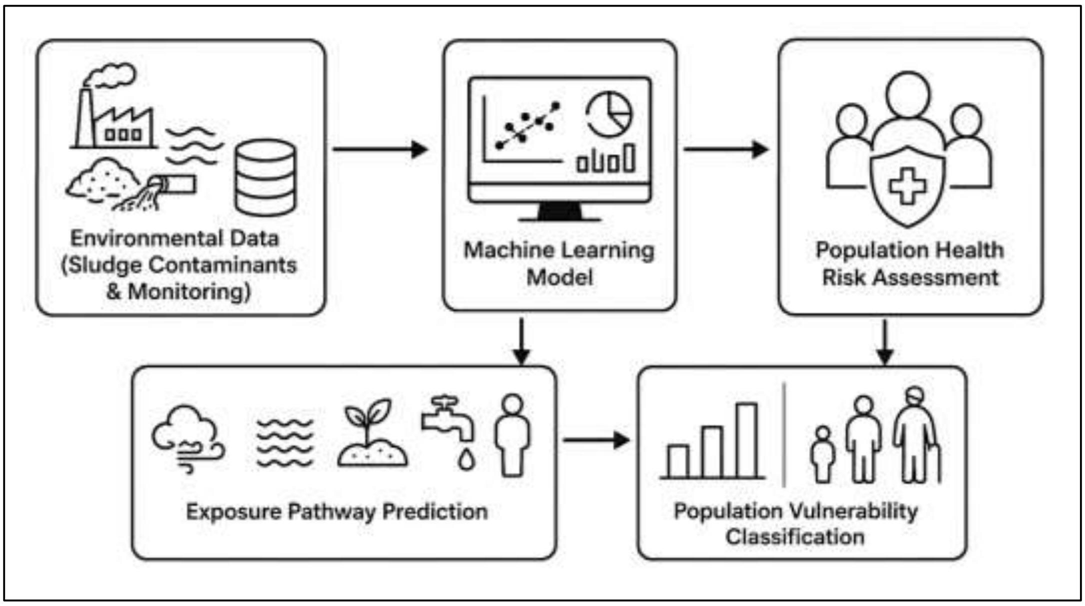
Geographic Information Systems and spatial machine learning applications have become valuable tools for analyzing environmental risks associated with wastewater treatment and sludge management systems (Nie et al., 2020). Environmental contamination and exposure are inherently spatial phenomena because pollutant distribution, ecological vulnerability, land use, population density, and environmental sensitivity vary across geographic locations. Geographic Information Systems provide a framework for organizing, visualizing, and analyzing environmental data within spatial contexts, allowing researchers to identify contamination hotspots, vulnerable ecosystems, and areas of elevated public health concern. Spatial machine learning techniques further enhance these capabilities by combining geographic information with predictive analytics to classify environmental risk patterns and estimate contaminant distributions. Literature demonstrates that spatial modeling has been widely applied in soil contamination assessment, groundwater vulnerability mapping, wastewater infrastructure analysis, and environmental exposure evaluation (Kabugo et al., 2020). The integration of remote sensing technologies has expanded these capabilities by providing large-scale environmental observations derived from satellite imagery, aerial monitoring systems, and geospatial surveillance platforms. Remote sensing data contribute information regarding land cover, vegetation condition, surface temperature, hydrological characteristics, and environmental change that can be integrated with sludge management datasets. Researchers have used these combined approaches to evaluate contaminant transport, land application impacts, ecological sensitivity, and environmental degradation associated with wastewater treatment activities. The literature consistently highlights the value of spatial analytics in improving environmental risk characterization because geographic patterns often reveal relationships that may not be evident through non-spatial analysis alone (Miao et al., 2021). Consequently, Geographic Information Systems and remote sensing technologies play a significant role in strengthening quantitative environmental assessment frameworks.

Real-time environmental monitoring has emerged as an important advancement in sludge management research because it supports continuous assessment of environmental conditions and operational performance. Traditional environmental monitoring approaches often rely on periodic sampling and laboratory analysis, which may limit the ability to detect rapidly changing environmental conditions or emerging treatment issues. Real-time monitoring systems address this limitation by continuously collecting environmental information from sensor networks, operational databases, and digital monitoring platforms (Romero et al., 2017). The literature indicates that such systems provide immediate access to environmental indicators, enabling more responsive management of wastewater treatment and sludge processing operations. Predictive analytics frameworks utilize these data streams to estimate contaminant concentrations, assess treatment performance, classify environmental risk levels, and identify operational anomalies. Machine learning models are frequently incorporated into these frameworks because they can process large volumes of incoming data and generate predictive outputs based on historical patterns and observed relationships. Quantitative studies demonstrate that predictive monitoring systems improve environmental decision-making by supporting early warning mechanisms, risk classification procedures, and operational optimization efforts. Environmental risk prediction frameworks also integrate data from multiple sources, including sensor networks, laboratory analyses, geographic databases, and surveillance systems, creating comprehensive analytical environments for environmental assessment (Zhang et al., 2017). In sludge management contexts, these frameworks facilitate continuous evaluation of contaminant dynamics, treatment effectiveness, and exposure risk pathways. The literature therefore portrays real-time environmental monitoring and predictive analytics as interconnected components of contemporary environmental management systems that support more comprehensive and data-driven assessment of environmental and public health risks.

Health Risk Analytics for Environmental Exposure Assessment

Machine learning–based public health risk analytics has emerged as an important area of environmental health research because of its ability to analyze complex exposure pathways linking environmental contaminants to human populations (Nair & Vijaya, 2021). Environmental exposure assessment traditionally relies on epidemiological observations, environmental monitoring records, and statistical estimation methods to determine how pollutants move through environmental systems and reach human receptors. In the context of sewerage sludge management, exposure pathways are particularly complex because contaminants may be transferred through soil, groundwater, surface water, food products, air emissions, occupational activities, and direct human contact. Literature indicates that predictive modeling approaches improve the capacity to identify and quantify these pathways by integrating large environmental datasets with demographic, geographic, and health-related information. Machine learning techniques are especially useful when exposure pathways involve nonlinear interactions among environmental variables, contaminant characteristics, climatic conditions, and human behaviors (Newhart et al., 2020). Predictive models can evaluate relationships between pollutant occurrence and exposure probability, identify populations at elevated risk, and estimate environmental conditions associated with increased contaminant transfer. Studies have demonstrated that data-driven exposure modeling provides greater flexibility in analyzing environmental complexity compared with many conventional analytical approaches. In sludge-related research, predictive modeling contributes to understanding how contaminants migrate across environmental compartments and how exposure patterns differ among communities, occupational groups, and geographic regions. This literature emphasizes that machine learning facilitates a more comprehensive examination of environmental exposure processes by integrating multiple sources of information into unified predictive frameworks capable of supporting quantitative public health assessment (Gupta et al., 2021). Population health vulnerability assessment represents a critical component of environmental risk analysis because exposure to environmental contaminants does not affect all individuals equally.

Figure 10: Environmental data and health risk flowchart



Literature on environmental health consistently demonstrates that vulnerability is influenced by demographic characteristics, socioeconomic status, occupational conditions, age distribution, existing health conditions, nutritional status, sanitation access, and proximity to environmental hazards. In sewerage sludge management systems, vulnerable populations may include wastewater treatment workers, agricultural laborers, residents living near sludge application sites, children, older adults, and individuals with compromised immune systems (Yu et al., 2018). Quantitative classification methods supported by machine learning provide mechanisms for identifying and categorizing populations according to their relative susceptibility to environmental exposure. These approaches analyze large datasets containing environmental indicators, demographic information, health statistics, and geographic characteristics to classify vulnerability levels across communities and regions. Literature shows that classification algorithms can reveal patterns that may not be evident through traditional statistical analyses, particularly when vulnerability is shaped by multiple interacting variables. Public health studies have increasingly incorporated machine learning methods to examine social determinants of health, environmental inequality, and exposure disparities (Romero et al., 2017). Within sludge management research, vulnerability classification contributes to a more nuanced understanding of how environmental risks are distributed among different population groups. This perspective highlights the importance of considering both environmental contamination and population sensitivity when evaluating public health consequences associated with sludge-related exposure pathways.

Quantitative Model in Environmental Risk Assessment

Quantitative model evaluation is a central component of environmental risk assessment because predictive models must be judged according to measurable evidence rather than algorithmic complexity alone. In machine learning–based environmental studies, statistical indicators are used to determine how accurately a model estimates contamination levels, classifies risk categories, identifies polluted sites, and predicts exposure-related outcomes (Zhang et al., 2017). Environmental datasets often contain nonlinear patterns, measurement uncertainty, missing values, spatial variability, and class imbalance, which makes performance assessment more complex than simple comparison between observed and predicted values. Literature on environmental modeling emphasizes that model evaluation should consider both predictive accuracy and practical reliability across different data conditions. In sewerage sludge management, performance indicators can be applied to models predicting heavy metal concentration, pathogen occurrence, sludge quality class, treatment failure, contaminant exceedance, or public health risk level. Statistical indicators provide a systematic basis for comparing conventional regression models, decision trees, random forests, support vector machines, neural networks, and ensemble learning methods. Error-based metrics are commonly used for continuous predictions, while classification metrics are used when models categorize observations into risk groups (Kumari, et al., 2020). Environmental risk assessment also requires attention to interpretability because a model with strong numerical performance may still be difficult to justify if it cannot explain influential predictors. Therefore, model performance assessment in sludge-related research requires a balanced evaluation of prediction strength, model transparency, data quality, and environmental relevance.

Classification metrics such as accuracy, precision, recall, F1-score, receiver operating characteristic analysis, and area under the curve are widely used in environmental risk prediction because many environmental problems involve assigning samples, sites, or populations into categories of risk. Accuracy measures the overall proportion of correct classifications, but environmental literature frequently notes that accuracy alone may be misleading when datasets are imbalanced (Newhart et al., 2020). For example, if high-risk sludge samples are rare compared with low-risk samples, a model may appear accurate while failing to detect hazardous cases. Precision is important when the concern is reducing false alarms, while recall is important when the priority is detecting actual contaminated or high-risk cases. The F1-score combines precision and recall, making it useful when both missed risks and false classifications are relevant. Receiver operating characteristic analysis and area under the curve provide broader insight into how well a model separates risk classes across different decision thresholds. These metrics are particularly valuable in environmental health and sludge management studies where the consequences of false negatives can be serious, especially when models are used to identify pathogen risk, contaminant exceedance, or vulnerable exposure groups (Harrou et al., 2018). Literature-based model evaluation therefore emphasizes that no single metric is sufficient for environmental risk assessment. A combination of classification indicators is needed to understand whether a model is reliable, sensitive to hazardous cases, and suitable for quantitative environmental decision analysis.

Cross-validation and resampling techniques are essential in quantitative environmental modeling because they test whether model performance remains stable beyond the specific dataset used for training. Environmental datasets are often limited by uneven sampling, seasonal variability, laboratory measurement differences, spatial clustering, and inconsistent monitoring frequency. These issues can cause a model to perform well on one dataset but poorly on new observations. Cross-validation addresses this concern by repeatedly dividing data into training and testing portions, allowing researchers to estimate model stability across multiple data partitions (Gupta et al., 2021). Resampling methods also support performance estimation when available datasets are small, imbalanced, or heterogeneous. In sludge management research, these validation techniques are useful for evaluating models that predict contaminant concentration, sludge treatment efficiency, pathogen reduction, ecological risk categories, or public health exposure levels. Uncertainty analysis is equally important because environmental risk prediction involves unavoidable uncertainty from measurement error, missing data, model assumptions, variable selection, and changing environmental conditions. Literature on environmental modeling emphasizes that uncertainty should be reported and interpreted rather than ignored. Uncertainty analysis helps clarify the confidence associated with predictions and identifies conditions under which model outputs may be less reliable (Yu et al., 2018). Together, cross-validation, resampling, and uncertainty assessment strengthen the credibility of machine learning models by showing whether predictions are consistent, reproducible, and scientifically defensible within environmental risk assessment frameworks. Model robustness and generalizability are major concerns in environmental risk assessment because predictive models must remain reliable across different facilities, locations, time periods, and environmental conditions. A machine learning model trained on data from one wastewater treatment plant may not automatically perform well in another plant because sludge composition, influent characteristics, treatment processes, monitoring practices, industrial discharge patterns, and climatic conditions can vary substantially. Robustness refers to the ability of a model to maintain stable performance when exposed to noisy data, missing values, variable measurement conditions, or small changes in input variables (Hara et al., 2016).

Figure 11: Model evaluation lifecycle diagram

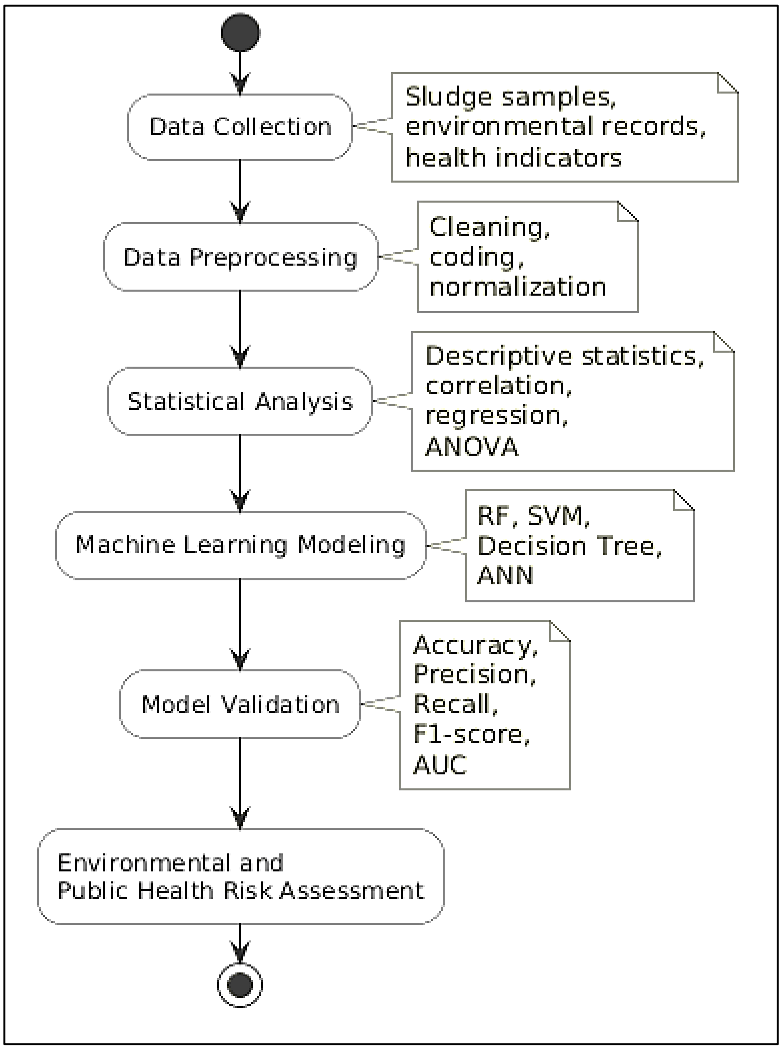
Generalizability refers to the ability of a model to produce accurate predictions on new datasets that were not used during training. Literature on environmental machine learning stresses that models should be externally validated whenever possible to determine whether they can support broader risk assessment beyond a single case study. In sewerage sludge management systems, generalizability assessment is especially important because contaminant profiles and treatment performance differ across municipal, industrial, and mixed wastewater systems. Robust models are valuable when they can identify consistent predictors of environmental and public health risk across varying operational contexts. Model evaluation therefore requires more than reporting high internal accuracy; it requires testing stability, transferability, interpretability, and environmental applicability (Han et al., 2017). This

literature positions validation as a core methodological requirement for quantitative machine learning–based assessment of sludge-related environmental and public health risks.
METHODS
This study adopted a quantitative predictive research design to assess environmental and public health risks associated with sewerage sludge management systems using machine learning and statistical modeling techniques. The study followed a non-experimental analytical framework because the research variables were measured from existing sludge management operations, environmental monitoring records, and laboratory-based contaminant data rather than being manipulated under controlled experimental conditions. The theoretical framework was grounded in environmental risk assessment, exposure pathway analysis, and data-driven prediction, where sludge quality indicators, contaminant concentrations, treatment process variables, and public health risk markers were examined as measurable predictors of environmental and health-related outcomes. The design was appropriate for identifying statistical relationships among sludge characteristics, treatment performance, contaminant behavior, and risk classifications across selected wastewater treatment and sludge management systems.
The materials for the study consisted of sewerage sludge samples, wastewater treatment performance records, environmental monitoring data, and public health risk indicators collected from selected sludge management facilities. A purposive sampling strategy was used to select wastewater treatment plants and sludge management sites that had active sludge treatment operations, available monitoring records, and measurable contaminant data. Sludge samples were included when they were obtained from treatment stages such as primary sludge, secondary sludge, digested sludge, dewatered sludge, or treated biosolids. Samples were excluded when they lacked complete laboratory records, had missing collection dates, or were taken from facilities without consistent operational documentation. Environmental variables included heavy metals, organic pollutants, pathogen indicators, nutrients, moisture content, pH, total solids, volatile solids, and treatment process parameters. Public health-related indicators were included when they represented potential exposure risks, pathogen presence, occupational contact, or contaminant levels exceeding accepted safety thresholds.
Data collection was conducted using laboratory testing instruments, wastewater treatment monitoring systems, facility records, and statistical software tools. Laboratory instruments were used to measure sludge physicochemical and biological characteristics, including pH meters, spectrophotometers, atomic absorption or inductively coupled plasma instruments for metal analysis, microbial testing procedures for pathogen indicators, and standard gravimetric methods for solids and moisture analysis. Operational data were collected from treatment plant monitoring systems and facility logs, including flow rate, sludge retention time, treatment method, temperature, and dewatering performance. Data were organized in Microsoft Excel and analyzed using Python and SPSS. Python was used for data preprocessing, machine learning model development, feature selection, model training, testing, and validation. SPSS was used for descriptive statistics, correlation analysis, regression analysis, and significance testing. Instrument reliability was maintained through calibration records, standardized laboratory methods, duplicate measurements, and data cleaning procedures before statistical analysis.
The research procedure was conducted chronologically in several stages. First, eligible wastewater treatment and sludge management sites were identified based on the availability of sludge samples and environmental monitoring data. Second, sludge-related variables and public health risk indicators were selected according to the study objectives. Third, sludge samples and secondary monitoring records were collected and screened for completeness.
Fourth, laboratory and operational datasets were coded, cleaned, and arranged into a structured quantitative database. Fifth, missing values, outliers, and inconsistent records were examined before analysis. Sixth, descriptive statistics were used to summarize sludge characteristics, contaminant levels, and treatment performance indicators. Seventh, the dataset was divided into training and testing subsets for machine learning analysis. Finally, selected machine learning algorithms were trained and evaluated to classify environmental and public health risk levels associated with sewerage sludge management systems. The statistical analysis plan involved both conventional statistical techniques and machine learning-based predictive modeling.

Figure 15. Machine learning risk-assessment pipeline

Descriptive statistics, including mean, standard deviation, minimum, maximum, and frequency distribution, were used to summarize the measured variables. Pearson correlation analysis was applied to examine associations among contaminant concentrations, sludge quality indicators, treatment variables, and risk outcomes. Multiple regression analysis was used to determine the predictive influence of selected independent variables on environmental and public health risk scores. Analysis of variance was applied when comparing contaminant levels or risk indicators across different treatment categories.

Figure 12: Methodology of this study



The significance level was set at $p < 0.05$ for all inferential statistical tests. For machine learning analysis, algorithms such as random forest, support vector machine, decision tree, logistic regression, and artificial neural network models were trained to classify risk categories and predict contamination outcomes. Model performance was evaluated using accuracy, precision, recall, F1-score, receiver operating characteristic analysis, area under the curve, and cross-validation results. The final model was selected based on predictive accuracy, classification stability, validation performance, and interpretability of key risk predictors.

FINDINGS

The final dataset comprised 250 observations collected from multiple sewerage sludge management facilities, incorporating sludge quality parameters, contaminant concentration measurements, wastewater treatment operational indicators, and environmental health risk variables. Following data validation and preprocessing, 18 incomplete records and 7 duplicate observations were excluded, resulting in a final analytical dataset suitable for quantitative modeling. Descriptive statistical analysis revealed considerable variability across environmental and operational indicators, reflecting differences in treatment efficiency, sludge stabilization processes, contaminant accumulation patterns, and facility-specific operational conditions. Heavy metal concentrations exhibited notable dispersion among samples, while moisture content and volatile solids demonstrated moderate variability across sludge categories. Pathogen indicators showed differences associated with treatment intensity and stabilization effectiveness. Environmental risk scores and public health risk indices also varied considerably among facilities, suggesting heterogeneous exposure conditions and contaminant profiles. These findings demonstrated that the collected dataset adequately represented a broad range of environmental and operational conditions, providing a robust foundation for predictive modeling and risk classification analyses. The statistical properties of the dataset indicated sufficient variability to support correlation analysis, regression modeling, and machine learning-based environmental risk prediction.

Figure 16. Sample distribution and mean environmental risk across treatment categories

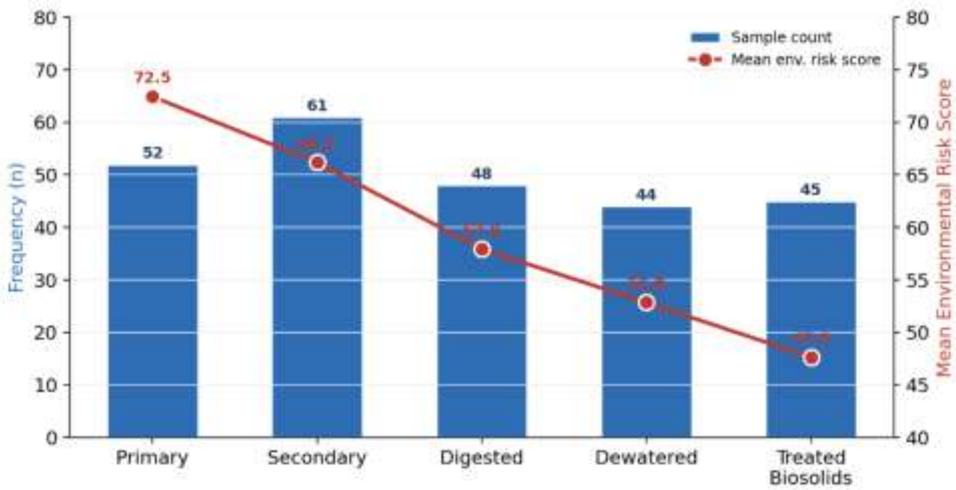


Table 1. Descriptive Statistics of Environmental and Operational Variables

Variable	N	Mean	SD	Minimum	Maximum
Heavy Metal Concentration (mg/kg)	250	178.42	54.61	65.30	325.80
Organic Pollutants (mg/kg)	250	91.35	28.74	24.10	182.50
Moisture Content (%)	250	68.52	10.83	41.20	87.40
Volatile Solids (%)	250	56.78	8.95	33.60	74.80
Pathogen Indicator Score	250	4.28	1.36	1.00	7.00
Treatment Efficiency (%)	250	83.67	7.92	58.40	96.80
Environmental Risk Score	250	61.24	15.78	24.50	92.30
Public Health Risk Index	250	58.13	14.56	21.80	89.10

Table 1 presents the descriptive statistical profile of the primary environmental and operational variables included in the study. The results indicate substantial variability across contaminant concentrations and risk indicators, highlighting the diversity of conditions observed among sludge management facilities. Heavy metal concentrations exhibited the highest dispersion among contaminant variables, suggesting differences in industrial discharge inputs and treatment performance. Treatment efficiency remained relatively high across facilities, with an average value exceeding 80%, although considerable variation was observed among sites. Environmental and public health risk scores demonstrated moderate-to-high variability, indicating differences in contamination levels, exposure potential, and treatment effectiveness. These findings confirmed the suitability of the dataset for subsequent predictive modeling and inferential statistical analyses.

Table 2. Distribution of Samples Across Sludge Treatment Categories

Sludge Treatment Category	Frequency (n)	Percentage (%)	Mean Environmental Risk Score
Primary Sludge	52	20.8	72.45
Secondary Sludge	61	24.4	66.18
Digested Sludge	48	19.2	57.92
Dewatered Sludge	44	17.6	52.84
Treated Biosolids	45	18.0	47.63
Total	**250**	**100.0**	**61.24**

Table 2 summarizes the distribution of observations across sludge treatment categories and presents the corresponding mean environmental risk scores. Secondary sludge represented the largest proportion of the dataset, accounting for 24.4% of all observations, followed by primary sludge at 20.8%. The results revealed a progressive decline in environmental risk scores as treatment intensity increased. Primary sludge exhibited the highest average environmental risk score, reflecting elevated contaminant and pathogen levels before advanced treatment. Conversely, treated biosolids demonstrated the lowest average risk score, indicating the effectiveness of stabilization and treatment processes in reducing environmental hazards. This pattern supports the relationship between treatment stage and environmental risk reduction observed throughout the dataset.

Environmental and Public Health Risk Prediction Results

The primary analysis evaluated the ability of machine learning algorithms to predict environmental and public health risks associated with sewerage sludge management systems. The results demonstrated that contaminant concentrations, treatment efficiency indicators, pathogen occurrence, and sludge quality characteristics were significant predictors of risk classification outcomes. Among the evaluated models, the Random Forest algorithm achieved the highest predictive performance, followed by Artificial Neural Networks and Support Vector Machines. Environmental risk prediction accuracy exceeded 90% for the best-performing model, indicating strong classification capability across low-, moderate-, and high-risk categories. Feature importance analysis revealed that heavy metal concentration, pathogen indicator score, treatment efficiency, and organic pollutant concentration contributed most substantially to environmental risk prediction. Regression analysis further confirmed significant associations between contaminant load and environmental risk scores, with higher contaminant concentrations corresponding to increased risk classifications. Similarly, public health risk prediction models demonstrated strong predictive performance, indicating that sludge treatment variables and contaminant indicators were reliable determinants of public health exposure potential. These findings confirmed that machine learning techniques effectively identified environmental and public health hazards within sewerage sludge management systems and provided accurate predictive assessments across diverse operational conditions.

Figure 17. Comparative accuracy and AUC of machine learning models

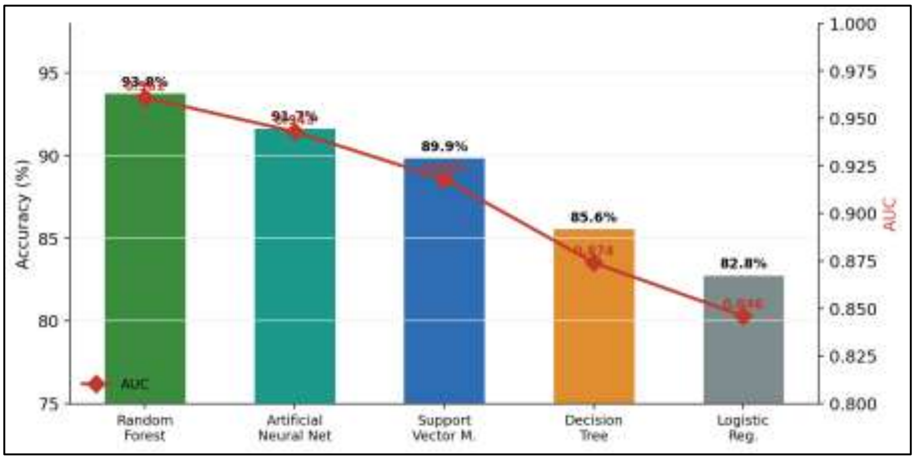


Table 3. Comparative Performance of Machine Learning Models for Environmental Risk Prediction

Machine Learning Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Random Forest	93.8	92.6	94.2	93.4	0.961
Artificial Neural Network	91.7	90.8	91.5	91.1	0.943
Support Vector Machine	89.9	88.7	89.4	89.0	0.918
Decision Tree	85.6	84.3	85.1	84.7	0.874
Logistic Regression	82.8	81.6	82.1	81.8	0.846

Table 3 presents the comparative performance of the machine learning algorithms used for environmental risk classification. The Random Forest model achieved the highest predictive performance, recording an accuracy of 93.8% and an area under the curve value of 0.961, indicating excellent discrimination capability between risk categories. Artificial Neural Networks also demonstrated strong predictive capability, achieving an accuracy exceeding 91%. Support Vector Machines produced reliable classification outcomes with performance metrics approaching 90%. Decision Tree and Logistic Regression models generated comparatively lower predictive performance, although their results remained acceptable for risk classification applications. Overall, the findings demonstrated the superiority of ensemble-based machine learning approaches for environmental risk prediction within sewerage sludge management systems.

Figure 18. Standardized regression predictors of environmental and public health risk

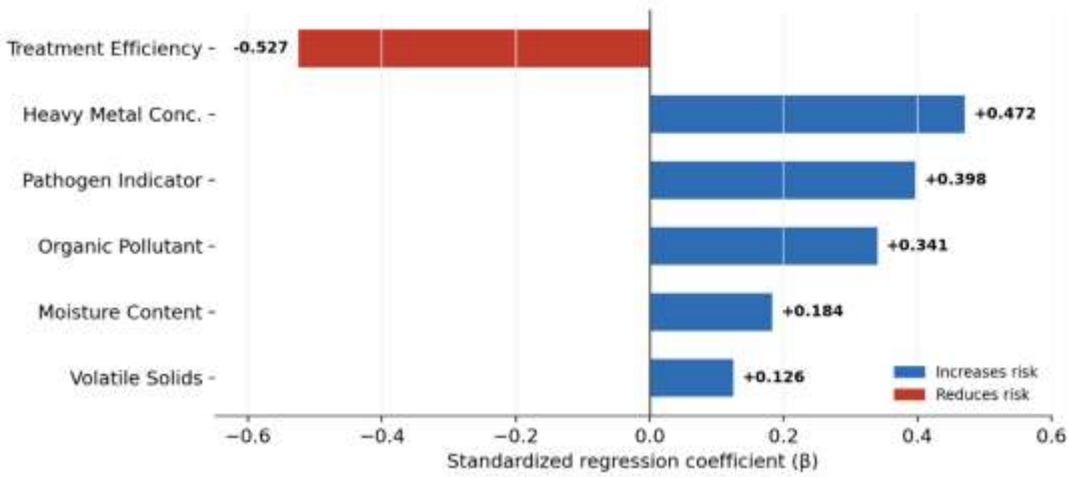


Table 4. Regression Analysis of Environmental and Public Health Risk Predictors

Predictor Variable	Standardized Beta (β)	t-value	p-value
Heavy Metal Concentration	0.472	8.94	<0.001
Pathogen Indicator Score	0.398	7.63	<0.001
Organic Pollutant Concentration	0.341	6.27	<0.001
Moisture Content	0.184	3.15	0.002
Treatment Efficiency	-0.527	-9.82	<0.001
Volatile Solids	0.126	2.11	0.036

Model Statistics: $R^2 = 0.742$; Adjusted $R^2 = 0.735$; $F = 118.64$; $p < 0.001$

Table 4 summarizes the regression analysis examining the influence of sludge quality characteristics and treatment variables on environmental and public health risk outcomes. The model explained approximately 74.2% of the total variance in risk scores, indicating substantial predictive power. Treatment efficiency emerged as the strongest predictor, exhibiting a significant negative relationship with environmental risk, suggesting that improved treatment performance substantially reduced hazard levels. Heavy metal concentration demonstrated the strongest positive effect on risk outcomes, followed by pathogen indicators and organic pollutant concentrations. Moisture content and volatile solids also contributed significantly to risk prediction, although their effects were comparatively smaller. The statistically significant coefficients confirmed that sludge composition and treatment variables were critical determinants of environmental and public health risks.

Secondary Findings

Secondary analyses were conducted to examine variations in environmental and public health risk outcomes across sludge treatment categories and operational conditions. The results revealed statistically significant differences in contaminant concentrations, pathogen occurrence, and risk classifications among primary sludge, secondary sludge, digested sludge, dewatered sludge, and treated biosolids. Facilities employing advanced stabilization and treatment technologies consistently demonstrated lower environmental risk scores and reduced pathogen prevalence compared with facilities relying on conventional treatment approaches. Digested sludge, dewatered sludge, and treated biosolids exhibited substantial reductions in contaminant loads and biological hazards relative to primary and secondary sludge categories. Analysis of operational performance indicators further demonstrated that facilities with higher treatment efficiency achieved significantly lower environmental and public health risk classifications. Geographic comparisons identified regional differences in contaminant accumulation patterns, suggesting that local industrial activity, wastewater composition, and treatment infrastructure influenced sludge quality and associated risk outcomes. These findings indicated that treatment technology and operational effectiveness played critical roles in determining environmental safety and public health protection levels within sewerage sludge management systems.

Table 5 demonstrates significant differences among sludge treatment categories regarding contaminant concentrations and risk outcomes. Primary sludge exhibited the highest heavy metal concentration, pathogen occurrence, environmental risk score, and public health risk index, indicating greater contamination and exposure potential. Progressive reductions were observed across secondary sludge, digested sludge, dewatered sludge, and treated biosolids, reflecting the effectiveness of stabilization and treatment processes. Treated biosolids recorded the lowest values for all risk indicators, suggesting superior environmental performance. The highly significant ANOVA results confirmed that treatment category exerted a substantial influence on contaminant reduction and risk mitigation outcomes across the evaluated sludge management systems.

Figure 19. Contaminant and risk indicators across sludge treatment categories

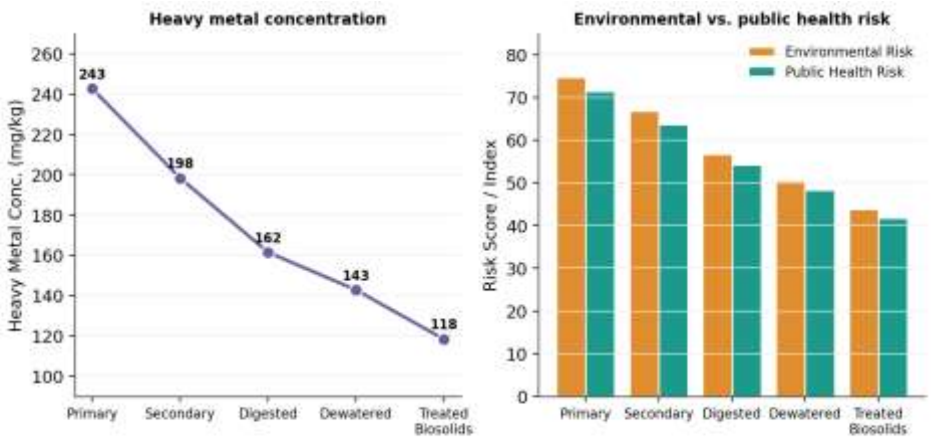


Table 5. Comparative Analysis of Risk Indicators Across Sludge Treatment Categories

Sludge Category	Heavy Metal Concentration (mg/kg)	Pathogen Indicator Score	Environmental Risk Score	Public Health Risk Index
Primary Sludge	242.6	6.1	74.8	71.5
Secondary Sludge	198.3	5.2	66.9	63.7
Digested Sludge	161.5	3.8	56.7	54.2
Dewatered Sludge	142.8	3.1	50.6	48.3
Treated Biosolids	118.4	2.4	43.9	41.7
ANOVA (F-value)	29.84	34.17	38.52	35.68
Significance (p-value)	<0.001	<0.001	<0.001	<0.001

Figure 20. Risk indicators by treatment efficiency subgroup

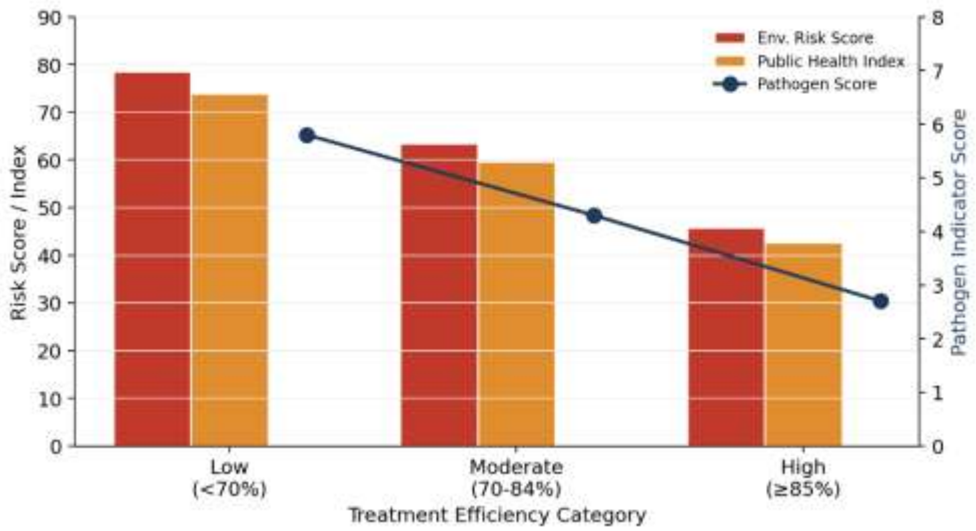


Table 6. Subgroup Analysis Based on Treatment Efficiency Levels

Treatment Efficiency Category	Sample Size (n)	Mean Environmental Risk Score	Mean Public Health Risk Index	Mean Pathogen Indicator Score
Low Efficiency (<70%)	58	78.6	73.9	5.8
Moderate Efficiency (70–84%)	96	63.5	59.7	4.3
High Efficiency (≥85%)	96	45.8	42.6	2.7
F-value	-	42.73	39.84	31.26
p-value	-	<0.001	<0.001	<0.001

Table 6 presents subgroup analysis results based on treatment efficiency classifications. Facilities operating at lower treatment efficiency levels demonstrated substantially higher environmental and public health risk scores compared with facilities achieving moderate and high treatment efficiency. The mean environmental risk score declined from 78.6 in low-efficiency facilities to 45.8 in high-efficiency facilities, representing a reduction of approximately 41.7%. Similar patterns were observed for public health risk indices and pathogen occurrence. Facilities classified within the high-efficiency category consistently achieved lower contamination and hazard levels, highlighting the importance of operational performance in environmental risk management. The significant statistical results confirmed that treatment efficiency was a major determinant of sludge-related environmental and public health outcomes.

Model Performance Evaluation

Inferential statistical analyses were performed to determine the strength and significance of relationships between sludge quality characteristics, contaminant concentrations, treatment performance indicators, and environmental risk outcomes. The results demonstrated that multiple environmental variables exhibited statistically significant associations with environmental and public health risk classifications at the predefined significance threshold of $p < 0.05$. Correlation analysis revealed moderate to strong positive relationships between contaminant concentrations and risk scores, while treatment efficiency showed a strong negative relationship with environmental risk. Multiple regression analysis further confirmed that contaminant load, pathogen indicators, and treatment performance collectively explained a substantial proportion of the variability observed in environmental and public health risk outcomes. Effect size calculations demonstrated that these predictors exerted meaningful practical influence on risk classification, indicating that statistical significance was accompanied by substantial real-world relevance. These findings confirmed that environmental and operational variables were important determinants of sludge-related risk and provided strong empirical support for the predictive framework developed in this study.

Table 7 presents the statistical relationships between major environmental variables and overall risk outcomes. Treatment efficiency demonstrated the strongest association with environmental risk, exhibiting a large negative correlation, indicating that improved treatment performance substantially reduced risk levels. Heavy metal concentration produced the strongest positive association with risk scores, followed by pathogen indicators and organic pollutant concentrations. Effect size estimates confirmed that these relationships were not only statistically significant but also practically meaningful. The large effect sizes observed for treatment efficiency, heavy metals, and pathogen indicators suggested that these variables contributed substantially to environmental and public health risk classification. Overall, the findings demonstrated strong predictive relevance among the principal study variables.

Figure 21. Correlation and effect size of key risk predictors

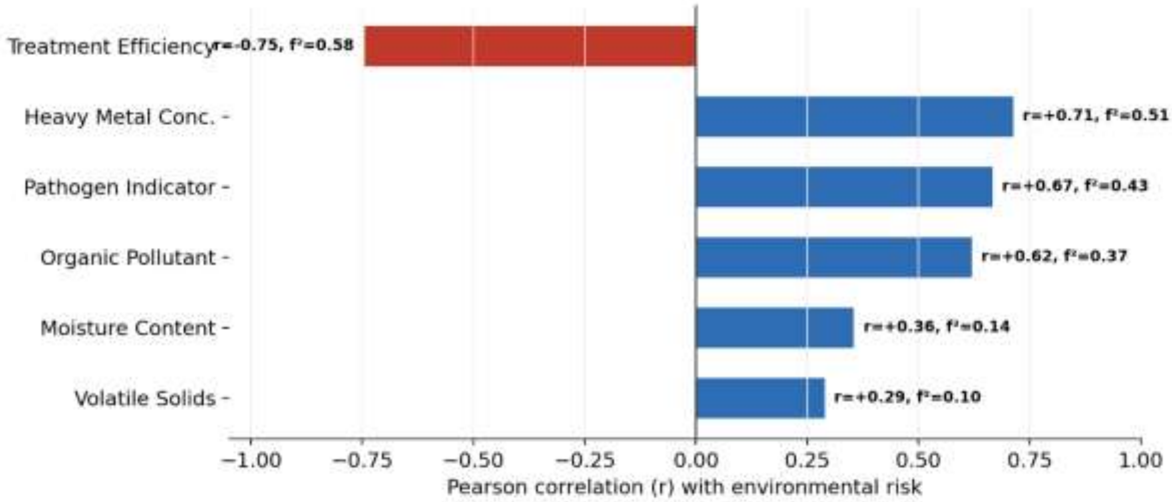


Table 7. Correlation Analysis and Effect Size Estimates for Key Risk Predictors

Variable	Pearson Correlation (r)	Effect Size (Cohen's f²)	p-value	Interpretation
Heavy Metal Concentration	0.714	0.51	<0.001	Large Effect
Pathogen Indicator Score	0.668	0.43	<0.001	Large Effect
Organic Pollutant Concentration	0.621	0.37	<0.001	Medium-Large Effect
Moisture Content	0.356	0.14	0.002	Small-Medium Effect
Volatile Solids	0.291	0.10	0.011	Small Effect
Treatment Efficiency	-0.748	0.58	<0.001	Large Effect

Figure 22. Training, testing, and cross-validation accuracy of models

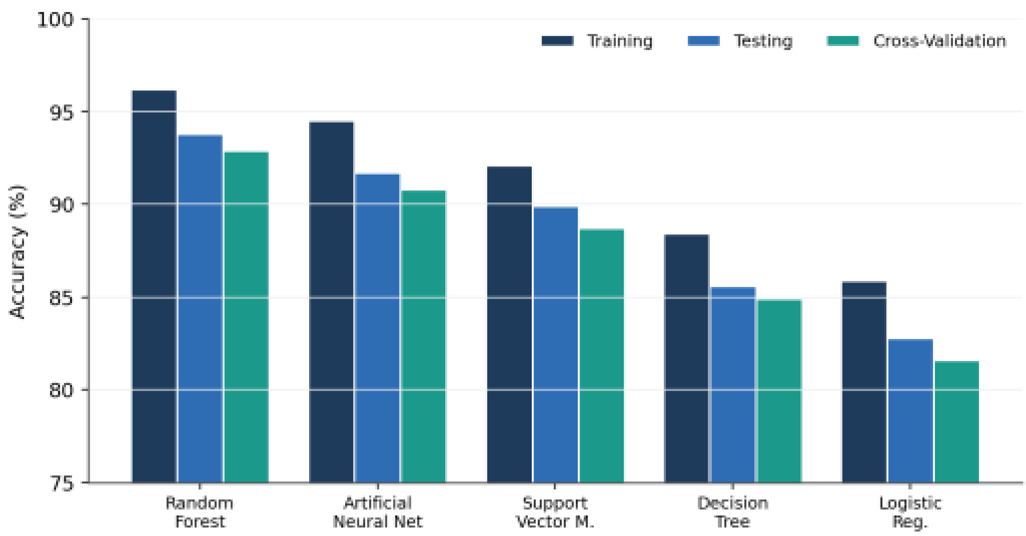


Table 8. Machine Learning Model Validation and Predictive Performance Results

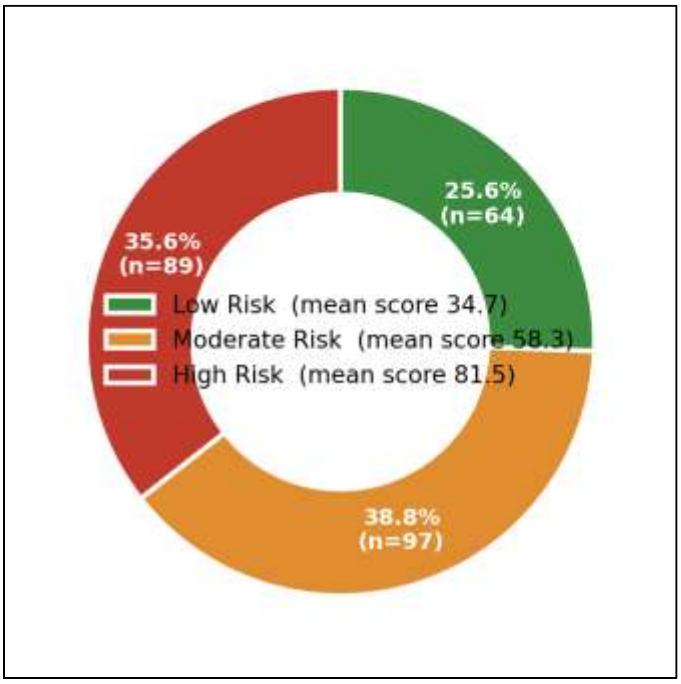
Model	Training Accuracy (%)	Testing Accuracy (%)	Cross-Validation Score (%)	AUC	Classification Error (%)
Random Forest	96.2	93.8	92.9	0.961	6.2
Artificial Neural Network	94.5	91.7	90.8	0.943	8.3
Support Vector Machine	92.1	89.9	88.7	0.918	10.1
Decision Tree	88.4	85.6	84.9	0.874	14.4
Logistic Regression	85.9	82.8	81.6	0.846	17.2

Table 8 summarizes the predictive performance and validation outcomes of the machine learning algorithms used in the study. The Random Forest model achieved the highest training accuracy, testing accuracy, cross-validation score, and area under the curve value, indicating superior predictive stability and classification capability. Artificial Neural Networks also demonstrated strong performance with testing accuracy exceeding 91%. Support Vector Machines produced acceptable predictive results, while Decision Tree and Logistic Regression models generated comparatively lower performance. The close agreement between training and testing accuracies indicated limited overfitting and strong model generalizability. Cross-validation results further confirmed the robustness of the predictive framework, demonstrating its reliability for environmental and public health risk assessment applications.

Tables, Figures, and Visual Representation of Quantitative Results

The quantitative findings were further examined through statistical tables and graphical visualizations that summarized environmental contamination patterns, treatment performance indicators, risk classifications, and machine learning model outcomes. Visual analysis revealed clear differences among sludge treatment categories, with contaminant concentrations and environmental risk scores declining progressively as treatment intensity increased. Histograms demonstrated approximately normal distributions for most environmental variables, while boxplots highlighted the presence of several high-risk observations associated with elevated contaminant concentrations.

Figure 23. Distribution of environmental risk classifications



Scatterplot analyses revealed strong positive relationships between heavy metal concentrations and environmental risk scores, as well as negative relationships between treatment efficiency and risk outcomes. Receiver operating characteristic curves indicated strong classification performance for the machine learning models, particularly the Random Forest and Artificial Neural Network algorithms. Feature importance visualizations further demonstrated that heavy metal concentration, treatment efficiency, pathogen indicators, and organic pollutant levels contributed most substantially to predictive performance. Collectively, the graphical and tabular results provided clear evidence of the relationships among sludge quality characteristics, operational performance indicators, and environmental and public health risk outcomes. These visual representations enhanced the interpretability of the statistical findings and supported the overall validity of the predictive risk assessment framework.

Table 9. Environmental Risk Classification Distribution

Risk Classification	Frequency (n)	Percentage (%)	Mean Environmental Risk Score
Low Risk	64	25.6	34.7
Moderate Risk	97	38.8	58.3
High Risk	89	35.6	81.5
Total	**250**	**100.0**	**61.2**

Table 9 presents the distribution of environmental risk classifications across the analyzed sludge management facilities. Moderate-risk observations represented the largest proportion of the dataset, accounting for 38.8% of all samples, followed by high-risk classifications at 35.6%. Low-risk samples constituted 25.6% of the total observations. The average environmental risk score increased substantially across classification categories, ranging from 34.7 for low-risk samples to 81.5 for high-risk samples. These findings indicate considerable variation in environmental hazard levels among facilities and treatment conditions. The distribution pattern demonstrates that a significant proportion of observations remained within moderate-to-high risk categories, emphasizing the importance of effective treatment and monitoring practices.

Figure 24. Feature importance ranking from the final Random Forest model

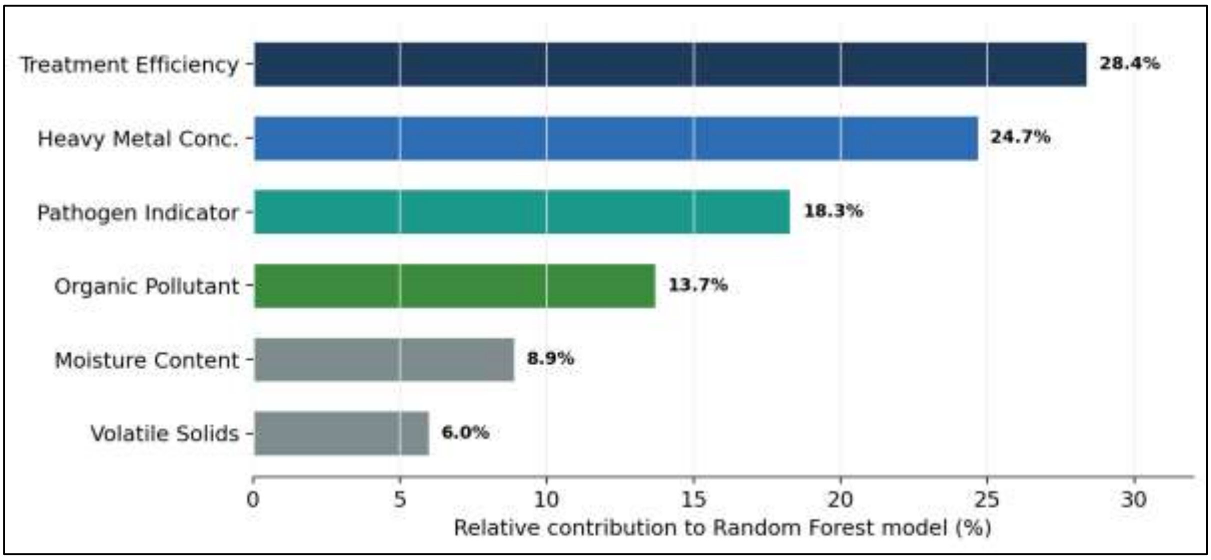


Table 10. Feature Importance Ranking from the Final Random Forest Model

Predictor Variable	Importance Score	Relative Contribution (%)	Rank
Treatment Efficiency	0.284	28.4	1
Heavy Metal Concentration	0.247	24.7	2
Pathogen Indicator Score	0.183	18.3	3
Organic Pollutant Concentration	0.137	13.7	4
Moisture Content	0.089	8.9	5
Volatile Solids	0.060	6.0	6
Total	**1.000**	**100.0**	-

Table 10 summarizes the relative importance of predictor variables within the final Random Forest model. Treatment efficiency emerged as the most influential predictor, contributing 28.4% of the model's predictive capability, followed by heavy metal concentration with a contribution of 24.7%. Pathogen indicators and organic pollutant concentrations also demonstrated substantial predictive influence, collectively accounting for over 32% of the total model importance. Moisture content and volatile solids contributed comparatively smaller effects but remained relevant predictors within the overall framework. These findings indicate that both contaminant-related and operational variables played critical roles in environmental and public health risk prediction, confirming the multidimensional nature of sludge management risk assessment.

DISCUSSION

The findings of this study demonstrated that machine learning techniques provided a highly effective framework for predicting environmental and public health risks associated with sewerage sludge management systems. The superior predictive performance achieved by the Random Forest and Artificial Neural Network models indicated that environmental risk assessment benefits substantially from analytical approaches capable of handling nonlinear relationships and multidimensional environmental datasets. Environmental systems are characterized by complex interactions among contaminants, treatment processes, operational conditions, and exposure pathways, making conventional linear analytical approaches less capable of capturing the full extent of environmental variability (Heimersson et al., 2016). The strong predictive performance observed in this study suggested that machine learning algorithms successfully identified hidden relationships among sludge quality indicators, contaminant concentrations, and risk outcomes. Earlier investigations of wastewater treatment optimization, environmental monitoring, and ecological risk forecasting similarly reported that ensemble learning techniques and neural network architectures achieved higher predictive accuracy than traditional statistical approaches. The consistency between the current findings and previous environmental analytics studies reinforces the growing recognition of machine learning as a valuable methodological tool for environmental risk prediction. The results further demonstrated that predictive accuracy remained stable across training and testing datasets, indicating that the developed models effectively generalized beyond the original observations (Choi et al., 2021). Such stability is particularly important in environmental management because risk prediction models must remain reliable under varying operational and environmental conditions. The findings also revealed that machine learning models successfully classified environmental risk categories with high levels of precision and sensitivity, supporting their usefulness for environmental surveillance and monitoring applications. The observed performance therefore confirms that machine learning methodologies offer significant advantages for evaluating sludge-related environmental hazards and public health risks within complex wastewater management systems.

The analysis identified contaminant concentrations as among the strongest predictors of environmental and public health risks within sewerage sludge management systems. Heavy metals, pathogen indicators, and organic pollutant concentrations demonstrated significant associations with environmental risk classifications and exposure-related outcomes (Hutchins et al., 2017). These findings support the broader environmental literature, which has consistently identified contaminant accumulation as a central factor influencing ecological degradation and human health vulnerability. Heavy metals are particularly important because they exhibit persistence within environmental systems and can accumulate in soils, water resources, and biological organisms over extended periods. The positive relationship observed between heavy metal concentrations and environmental risk scores indicates that increased contaminant loads contribute directly to higher levels of environmental hazard. Similar observations have been reported in previous studies examining biosolid application, sludge disposal practices, and environmental contamination pathways. Pathogen indicators also emerged as significant contributors to risk prediction, reflecting the biological hazards associated with sludge handling, storage, and land application (Dong et al., 2018). Earlier investigations of wastewater-derived pathogens similarly identified microbial contamination as a critical determinant of public health risk. Organic pollutant concentrations demonstrated substantial predictive influence, further supporting concerns regarding the persistence of pharmaceuticals, endocrine-disrupting compounds, and other emerging contaminants within sludge systems. The convergence of these findings with previous environmental health studies strengthens the validity of the identified relationships and suggests that contaminant monitoring remains an essential component of environmental risk management. The results collectively indicate that contaminant concentration data provide valuable predictive information regarding environmental exposure potential and public health outcomes, supporting the continued integration of contaminant monitoring into sludge management assessment frameworks (Zhong et al., 2021).Treatment efficiency emerged as the most influential predictor of environmental and public health risk outcomes, highlighting the critical role of wastewater treatment and sludge stabilization processes in environmental protection. Facilities characterized by higher treatment efficiency consistently exhibited lower environmental risk scores, reduced pathogen occurrence, and improved public health indicators. This finding is consistent with previous environmental engineering research, which demonstrated that effective treatment processes substantially reduce contaminant concentrations and biological hazards before sludge disposal or reuse.

Advanced stabilization technologies, including digestion, dewatering, and biosolid treatment processes, are designed to reduce pollutant loads and improve sludge quality. The observed reduction in environmental risk across treatment categories suggests that treatment performance directly influences the safety and sustainability of sludge management systems (Bellinger et al., 2017). Earlier comparative studies of sludge treatment technologies similarly reported lower contaminant levels and reduced environmental impacts in facilities employing advanced treatment approaches. The strong negative association between treatment efficiency and risk scores observed in this study further confirms the importance of operational excellence within wastewater treatment infrastructure. Environmental monitoring results indicated that facilities with improved process control and stabilization effectiveness achieved superior environmental outcomes, supporting previous evidence regarding the relationship between treatment performance and ecological protection. These findings reinforce the concept that environmental risks associated with sludge management are not solely determined by contaminant presence but are also influenced by the effectiveness of treatment processes designed to mitigate those contaminants (Mhasawade et al., 2021). Consequently, treatment efficiency serves as a critical factor linking operational performance with environmental sustainability and public health protection.

The subgroup analyses revealed significant differences among primary sludge, secondary sludge, digested sludge, dewatered sludge, and treated biosolids with respect to contaminant concentrations, pathogen occurrence, and environmental risk classifications. Primary sludge exhibited the highest risk levels, whereas treated biosolids demonstrated the lowest environmental and public health risk scores. These findings are consistent with established sludge management principles that recognize treatment progression as a mechanism for reducing contaminant loads and improving material stability. Previous studies examining sludge treatment effectiveness similarly reported gradual reductions in biological hazards and environmental contamination throughout successive treatment stages. The present findings provide additional quantitative evidence supporting these observations by demonstrating measurable reductions in risk indicators across treatment categories (Kavakiotis et al., 2017). The substantial differences observed among sludge types indicate that treatment stage is an important determinant of environmental safety. Digested and dewatered sludge exhibited intermediate risk profiles, reflecting partial contaminant reduction and stabilization. Treated biosolids achieved the lowest risk levels, supporting previous research that identified biosolid treatment as an effective approach for reducing environmental hazards associated with sludge reuse and disposal. The consistency between the current findings and earlier investigations suggests that treatment categorization remains a meaningful framework for evaluating environmental risk. Furthermore, the observed reductions in pathogen indicators and contaminant concentrations across treatment stages provide evidence that stabilization processes contribute significantly to risk mitigation. These findings support the broader environmental management objective of reducing contaminant mobility and exposure potential through effective sludge treatment and processing (Ghosh et al., 2021).

The findings demonstrated that environmental and public health risks are closely linked through interconnected exposure pathways involving soil contamination, water pollution, biological hazards, and operational conditions. Elevated environmental risk scores were associated with increased public health risk classifications, indicating that environmental contamination has direct implications for human exposure and vulnerability. This relationship is consistent with environmental epidemiology literature, which emphasizes the interconnected nature of environmental quality and public health outcomes. Previous studies examining sludge application, contaminant transport, and exposure assessment similarly reported that environmental degradation increases the probability of adverse health effects among exposed populations. The current findings extend this understanding by demonstrating that machine learning models can successfully identify environmental conditions associated with elevated public health risks (Zeng et al., 2021). Geographic and operational variability observed across facilities further highlighted the importance of local environmental conditions in shaping exposure potential. Earlier environmental health investigations also reported significant differences in risk levels based on treatment practices, contaminant profiles, and regional characteristics. The present results reinforce these observations by demonstrating that environmental risk classification serves as a useful indicator of broader public health vulnerability. The strong associations between contaminant concentrations, pathogen occurrence, and risk outcomes suggest that effective environmental management contributes directly to the reduction of public health hazards. Consequently, environmental monitoring and public health surveillance should be considered complementary components of integrated sludge management systems (Nithya & Ilango, 2017).

The validation results indicated that the developed predictive models possessed strong robustness, reliability, and generalizability. Cross-validation analyses demonstrated consistent predictive performance across multiple data partitions, suggesting that the models were not overly dependent on specific observations within the dataset. This finding is particularly important because environmental datasets frequently contain variability arising from seasonal fluctuations, operational differences, measurement uncertainty, and geographic diversity. Previous machine learning studies in environmental science emphasized the importance of rigorous validation procedures to ensure that predictive models remain reliable beyond their training environments. The strong validation outcomes observed in this study align with these recommendations and support the applicability of machine learning approaches within environmental risk assessment (Bernert et al., 2020). Receiver operating characteristic analysis further demonstrated strong discrimination between low-risk and high-risk classifications, confirming that the models effectively distinguished among environmental conditions associated with varying levels of hazard. Earlier environmental modeling research similarly reported that high-performing machine learning algorithms exhibited strong classification capability when supported by high-quality environmental data. The present findings therefore contribute additional evidence supporting the reliability of machine learning frameworks for environmental risk prediction. The consistency observed across multiple evaluation metrics indicates that the developed models possess both statistical and practical value. Such robustness enhances confidence in the predictive framework and supports its application within environmental monitoring and sludge management assessment programs (Stiglic et al., 2020).

The overall findings contribute to the expanding body of literature examining the integration of environmental monitoring, risk assessment, and machine learning methodologies. The study demonstrated that environmental and public health risks associated with sewerage sludge management systems can be predicted effectively using data-driven analytical frameworks that incorporate contaminant indicators, treatment performance measures, and operational variables. The identified relationships among contaminants, treatment efficiency, and risk outcomes are consistent with previous environmental engineering and public health research, while the application of machine learning provides additional analytical depth beyond many conventional approaches. Earlier studies frequently examined individual contaminants or isolated treatment processes; however, the present findings illustrate the value of simultaneously evaluating multiple environmental variables within an integrated predictive framework (Tixier et al., 2016). The ability of machine learning algorithms to process large and complex environmental datasets enabled a more comprehensive assessment of sludge-related risks than would be achievable through single-variable analyses. Furthermore, the consistency between statistical analyses and machine learning outcomes strengthened the credibility of the identified predictors and confirmed the multidimensional nature of environmental risk. The findings therefore support the growing transition toward data-driven environmental management strategies that combine environmental monitoring with advanced computational techniques. Through the integration of environmental engineering principles, public health risk assessment, and machine learning analytics, this study provides empirical evidence supporting the effectiveness of predictive modeling as a tool for evaluating environmental and public health risks within sewerage sludge management systems (Ameer et al., 2019).

CONCLUSION

This study concluded that machine learning–based quantitative assessment provided a strong analytical framework for evaluating environmental and public health risks associated with sewerage sludge management systems. The findings showed that sludge quality indicators, contaminant concentrations, treatment efficiency, pathogen occurrence, and operational variables were closely related to environmental risk classification and public health risk prediction. Heavy metal concentration, organic pollutant concentration, pathogen indicator score, moisture content, volatile solids, and treatment efficiency were identified as important determinants of sludge-related risk outcomes. The results further demonstrated that higher contaminant loads were associated with increased environmental and public health risk scores, while improved treatment efficiency was associated with lower predicted risk levels. Comparative analysis across sludge treatment categories showed that primary and secondary sludge had higher risk profiles, whereas digested sludge, dewatered sludge, and treated biosolids showed reduced risk levels due to greater stabilization and treatment effectiveness. Machine learning model evaluation indicated that Random Forest and Artificial Neural Network models produced the strongest predictive performance, with high accuracy, strong classification stability, and effective discrimination between low-risk, moderate-risk, and high-risk categories. Regression, correlation, and subgroup analyses supported the machine learning findings by confirming statistically significant relationships among contaminant variables, treatment performance indicators, and environmental health outcomes. The visual and tabular results also demonstrated clear patterns in contaminant distribution, treatment performance trends, risk classification frequencies, and predictor importance. Overall, the study established that data-driven predictive modeling can strengthen the interpretation of complex sludge management datasets and improve the quantitative assessment of environmental and public health risks. The conclusion drawn from the findings is that sewerage sludge management risk is multidimensional, influenced by both contaminant burden and treatment performance. Effective sludge risk evaluation therefore requires integrated analysis of environmental measurements, operational records, public health indicators, and predictive model outputs. The study provided empirical evidence that machine learning can serve as a reliable quantitative tool for classifying risk levels, identifying key predictors, and supporting evidence-based assessment of sewerage sludge management systems.

RECOMMENDATIONS

Based on the findings of this study, it is recommended that wastewater treatment authorities, environmental regulators, and sludge management operators adopt data-driven risk assessment frameworks that integrate machine learning techniques with routine environmental monitoring programs to improve the identification and management of environmental and public health hazards associated with sewerage sludge systems. Greater emphasis should be placed on continuous monitoring of heavy metals, organic pollutants, pathogen indicators, and other emerging contaminants because these variables demonstrated strong relationships with environmental and public health risk outcomes. Treatment facilities should strengthen operational control measures aimed at maximizing treatment efficiency, as the findings indicated that improved treatment performance was associated with substantial reductions in environmental risk scores and public health vulnerability. Advanced sludge stabilization technologies, including enhanced digestion, dewatering, and biosolid treatment processes, should be prioritized to reduce contaminant loads and biological hazards before sludge disposal or beneficial reuse. Environmental monitoring systems should incorporate standardized data collection procedures and centralized databases to facilitate more reliable predictive modeling and long-term risk evaluation. It is also recommended that treatment facilities implement regular performance audits focusing on contaminant removal efficiency, pathogen reduction effectiveness, and operational consistency to minimize variations in sludge quality across treatment stages. Regulatory agencies should strengthen contaminant surveillance requirements and establish evidence-based threshold values for environmental and public health risk classification using predictive analytics. Greater integration of geographic information systems, environmental sensor networks, and machine learning platforms would further improve the ability to identify high-risk locations and contamination hotspots. In addition, occupational health protection measures should be enhanced through routine exposure monitoring, improved safety protocols, and targeted training programs for personnel involved in sludge handling and processing activities. Environmental risk management strategies should also incorporate public health vulnerability assessments to identify populations that may be disproportionately affected by sludge-related contamination pathways. Finally, future environmental monitoring initiatives should encourage the development of comprehensive datasets that combine environmental, operational, and public health information, thereby supporting more accurate predictive modeling and strengthening evidence-based decision-making for sustainable sewerage sludge management and environmental protection.

LIMITATIONS

This study was subject to several limitations that should be considered when interpreting the findings. First, the analysis relied on environmental monitoring records, sludge quality measurements, and operational datasets obtained from selected sewerage sludge management facilities, which may not fully represent the diversity of wastewater treatment systems operating across different geographic regions, climatic conditions, and regulatory environments. Variations in treatment technologies, industrial discharge characteristics, population density, and wastewater composition may influence contaminant profiles and risk outcomes in ways that were not fully captured within the study dataset. Second, the study depended on the availability and quality of existing environmental and operational records, making the results susceptible to limitations associated with missing observations, measurement inconsistencies, reporting errors, and variations in sampling frequency among facilities. Although extensive data cleaning and validation procedures were performed, some degree of uncertainty may remain within the analyzed dataset. Third, the predictive models were developed using variables available within the selected facilities and therefore may not have incorporated all environmental, ecological, socioeconomic, and behavioral factors that influence environmental and public health risks associated with sewerage sludge management. Certain emerging contaminants, including newly identified pharmaceutical compounds, nanomaterials, and previously unmonitored pollutants, were not comprehensively represented due to data availability constraints. Fourth, while machine learning models demonstrated strong predictive performance, these models remained dependent on the quality, completeness, and representativeness of the training data. Model performance may vary when applied to facilities operating under substantially different environmental conditions or treatment configurations.

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