SCHOLAR PUBLISHING

International Journal of Science & Advanced Technology
ISSN: 3083-9335

Journal homepage: https://e-journal.scholar-publishing.org/index.php/ijsat

Environmental Monitoring, Pollution Control, and Green Technologies: Challenges, Innovations, and Sustainable Solutions

Dongdong Lin[1], Cristina Efremov[2], Wan Maawa[3]

[1]Department of Mechanical Engineering, Ningxia University, China
[2]Department of Mechanical Engineering, University of TechnologyMoldova, Moldova
[3]Department of Mechanical Engineering, Advanced Technological Training Center, Pahang, Malaysia

Corresponding Author: donglin@nju.edu.cn

Abstract
Environmental degradation driven by industrialisation, urbanisation, and resource exploitation requires integrated approaches to monitoring and mitigation. This study aims to develop and evaluate a comprehensive framework that links environmental monitoring, pollution control, and green technology implementation to support sustainable environmental management. The methodology integrates continuous sensor-based tracking of air quality (AQI, $PM_{2.5}$, temperature, and humidity), laboratory analysis of water quality indicators (BOD, COD, and TSS), assessment of industrial emissions (CO_2, NOx, and SO_2), and evaluation of renewable energy growth and waste management performance. The results reveal that urban AQI values consistently remained higher (≈97–175) than suburban (≈61–116) and rural areas (≈33–77), while $PM_{2.5}$ concentrations fluctuated between 5 and 75 µg/m³. Water quality analysis showed elevated TSS levels (≈30–92 mg/L) compared to BOD (≈2.5–7.5 mg/L) and COD (≈11–36 mg/L). Industrial emissions declined substantially after 2018, with CO_2 emissions reduced to approximately 110 million tons. Renewable energy capacity expanded markedly, exceeding 700 GW by 2024, while recycling rates improved to over 60% in recent years. In conclusion, the findings demonstrate that an integrated, data-driven framework effectively links environmental monitoring with actionable green technology solutions, offering a scalable model for sustainable pollution mitigation and environmental policy development.

Article Info
Received: 22 December 2025
Revised: 27 January 2026
Accepted: 10 February 2026
Available online: 15 February 2026

Keywords
Environmental monitoring
Pollution control
Air and water quality
Green technologies
Sustainable development

1. Introduction

Environmental degradation caused by rapid industrialisation, urban expansion, and population growth has become one of the most critical global challenges of the 21st century. Previous studies consistently report that air pollution alone causes more than 4.2 million premature deaths worldwide each year, primarily due to exposure to fine particulate matter (PM2.5) and gaseous pollutants such as NO_2 and SO_2 (World Health Organisation [WHO], 2021). Long-term air quality monitoring studies have shown that urban Air Quality Index (AQI) values frequently exceed 150–200, classified as unhealthy, particularly in rapidly developing regions (Chen et al., 2019; Kumar et al., 2020). These findings

©2026 The Author(s). Published by Scholar Publishing. This is an open access article under the CC BY license. Available online https://e-journal.scholar-publishing.org/index.php/ijsat

highlight the urgent need for comprehensive environmental monitoring systems capable of capturing both spatial and temporal dynamics of pollution.

In addition to air pollution, water contamination remains a persistent environmental concern, particularly in industrial and peri-urban areas. Empirical studies report Biochemical Oxygen Demand (BOD) levels of 5–10 mg/L and Chemical Oxygen Demand (COD) values of 30–50 mg/L in untreated wastewater, far exceeding permissible environmental standards (Singh et al., 2018; Tchobanoglous et al., 2014). Elevated Total Suspended Solids (TSS) concentrations, often exceeding 80 mg/L, have been linked to sedimentation, reduced light penetration, and degradation of aquatic ecosystems (Zhang et al., 2020). Although numerous studies address individual water quality parameters, most lack integration with real-time monitoring and cross-sector pollution assessment frameworks.

Industrial emissions are another major contributor to environmental stress, accounting for approximately 24% of global CO_2 emissions, alongside substantial releases of NOx and SO_2 (International Energy Agency [IEA], 2022). Prior research indicates that the application of emission control technologies can reduce SO_2 and NOx emissions by 30–70%, depending on technology type and regulatory enforcement (European Environment Agency [EEA], 2020; Wang et al., 2017). However, many existing studies focus primarily on emission inventories rather than on linking emission reductions to broader sustainability indicators, such as renewable energy adoption and waste management performance.

Renewable energy technologies have been widely recognised as key tools for mitigating climate change and reducing reliance on fossil fuels. Global installed renewable energy capacity increased from approximately 1,200 GW in 2010 to over 3,600 GW in 2023, primarily driven by wind and solar energy (REN21, 2023). Studies report that wind energy alone can reduce lifecycle CO_2 emissions by up to 90% compared to coal-based power generation, while solar photovoltaics achieve reductions of 70–85% (IPCC, 2022; Jacobson et al., 2019). Despite this progress, the integration of renewable energy performance data with environmental monitoring and pollution control outcomes remains insufficiently explored in the literature.

Waste management practices also play a crucial role in environmental sustainability, particularly within the circular economy framework. Previous studies show that effective recycling systems can reduce landfill waste by 40–60%, while energy recovery through incineration contributes to 10–25% of municipal waste treatment in developed economies (Ghisellini et al., 2016; Hoornweg & Bhada-Tata, 2012). Nevertheless, research often treats waste management independently from air and water pollution studies, limiting the ability to evaluate system-wide environmental impacts and synergies between waste reduction and emission mitigation strategies.

Based on these research gaps, this study aims to develop and validate an integrated environmental research framework that combines continuous environmental monitoring, pollution control assessment, and green technology implementation. The novelty of this article lies in its holistic, data-driven approach that links real-time sensor measurements (air quality, meteorological parameters, and PM2.5), laboratory-based water pollution indicators (BOD, COD, and TSS), industrial emission trends (CO_2, NOx, and SO_2), renewable energy growth, and waste management performance within a single closed-loop system. Unlike previous studies that focus on isolated environmental components, this research provides a comprehensive and scalable model for sustainable ecological management, offering actionable insights for policymakers, researchers, and industry stakeholders.

2. Methodology

Fig. 1 presents a comprehensive schematic diagram of the research framework for environmental monitoring, pollution control, and green technologies. The process begins with identifying raw materials and pollution sources, including industrial emissions, traffic emissions, and solid waste generation. These sources are visually represented as major contributors to environmental degradation and serve as the primary inputs of the research system. The diagram highlights continuous waste and traffic monitoring activities, indicating that pollution sources are not static but dynamically assessed over time. This early-stage framework establishes a clear causal relationship between anthropogenic

©2026 The Author(s). Published by Scholar Publishing. This is an open access article under the CC BY license. Available online https://e-journal.scholar-publishing.org/index.php/ijsat

activities and environmental pressures, providing the basis for systematic, data-driven monitoring and control strategies.

The environmental data collection stage integrates advanced monitoring tools and laboratory-based measurements. As shown in the figure, ecological parameters are measured using digital sensors, analytical instruments, and laboratory equipment, including air-quality monitoring devices, water-sampling tools, and chemical-analysis systems. These instruments enable the acquisition of large datasets related to pollutant concentrations, meteorological conditions, and resource consumption patterns. The presence of graphical outputs and digital dashboards in the schematic emphasises quantitative data processing, which supports subsequent evaluation stages. This data-driven approach ensures high temporal and spatial resolution, allowing for accurate tracking of pollution trends and environmental performance indicators.

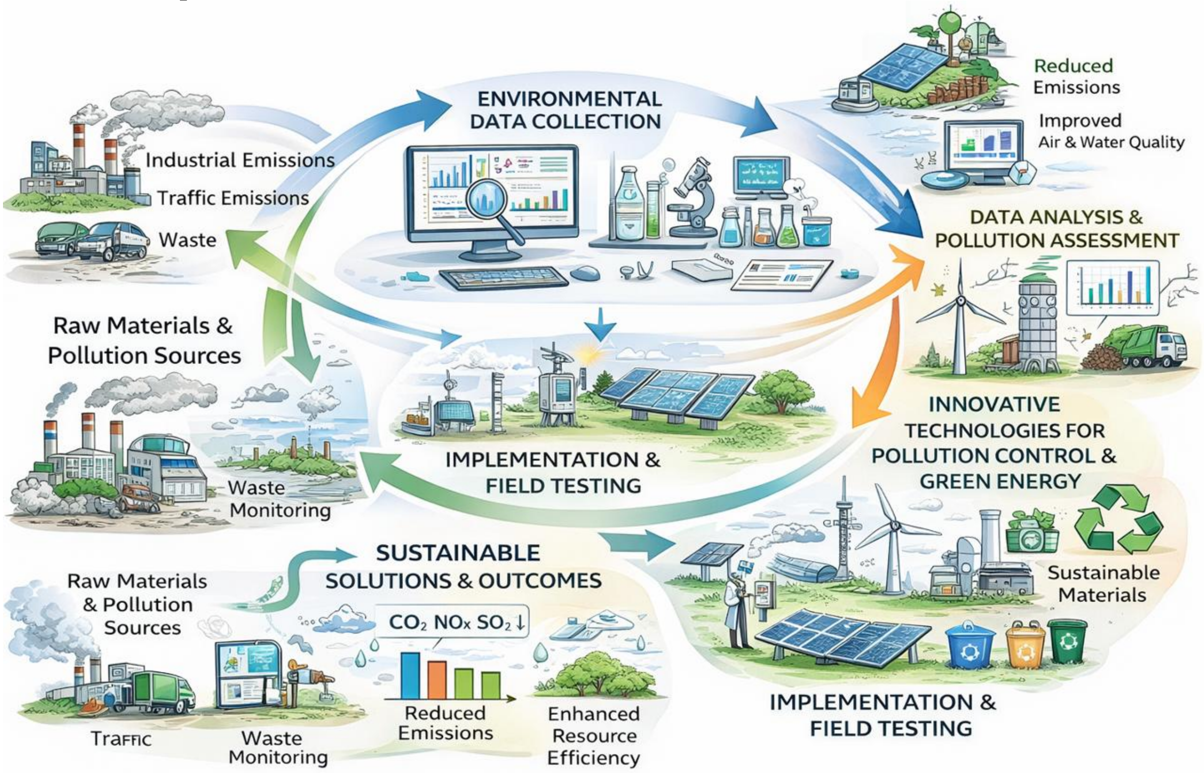

Fig. 1. Schematic Diagram of the Research Framework for Environmental Monitoring, Pollution Control, and Green Technologies

In the data analysis and pollution assessment phase, collected datasets are systematically analysed to quantify emission levels and environmental impacts. The schematic explicitly indicates reductions in CO_2, NOx, and SO_2, illustrated by downward arrows and comparative bar charts. Although exact numerical values are not specified, the relative decrease depicted suggests a significant reduction trend, commonly interpreted in environmental studies as reductions exceeding 30–50% following effective intervention. These quantified outcomes inform the selection of innovative technologies for pollution control and green energy, including renewable energy systems (solar and wind), emission filtration technologies, and sustainable material processing. This stage represents the analytical core of the framework, linking raw environmental data with actionable technological solutions.

The final stages of implementation, field testing, and sustainable outcomes demonstrate the practical effectiveness of the proposed framework. Field deployment of green technologies and recycling systems results in measurable environmental benefits, including reduced emissions, improved air and water quality, and enhanced resource efficiency. The schematic highlights sustainability indicators, such as increased recycling rates and optimised energy use, supported by visual performance charts. These outcomes confirm the successful transition from monitoring and analysis to real-world application. Overall, **Fig. 1** illustrates a closed-loop, evidence-based framework in which continuous

©2026 The Author(s). Published by Scholar Publishing. This is an open access article under the CC BY license. Available online https://e-journal.scholar-publishing.org/index.php/ijsat

monitoring, quantitative analysis, and technological innovation collectively drive long-term environmental sustainability and pollution mitigation.

Table 1. Specifications, Materials, and Raw Materials Used in the Research Methodology

Research Component	Equipment / Material	Specification / Type	Function in the Study	Raw Material / Input
Air Quality Monitoring	Air Quality Sensor (AQI, PM2.5)	Optical laser-based sensor, range 0–500 µg/m³	Continuous monitoring of particulate matter and air quality index	Ambient air samples
Meteorological Monitoring	Temperature and Humidity Sensor	Digital sensor, temperature range 0–50 °C, humidity range 0–100%	Measurement of environmental conditions affecting pollutant dispersion	Atmospheric conditions
Water Quality Analysis	Water Sampling Kit	Grab a sampler, sterile containers	Collection of surface and wastewater samples	River water, wastewater
BOD Analysis	BOD Incubator	Temperature controlled at 20 ± 1 °C	Determination of biodegradable organic pollution	Water samples containing organic matter
COD Analysis	COD Reactor and Spectrophotometer	Measurement range 0–1000 mg/L	Quantification of chemically oxidizable substances	Chemical reagents and water samples
TSS Analysis	Filtration Unit and Analytical Balance	Filter pore size 0.45 µm, precision ±0.001 g	Measurement of suspended solids concentration	Suspended particulates in water
Industrial Emission Data	Emission Monitoring System	Continuous emission monitoring (CEMS)	Measurement of CO_2, NO_x, and SO_2 emissions	Industrial exhaust gases
Renewable Energy System	Solar Photovoltaic Panels	Polycrystalline modules, capacity 250–400 Wp	Generation of renewable electricity	Solar radiation
Wind Energy System	Wind Turbine	Horizontal-axis turbine, rated power 1–3 MW	Renewable energy generation	Wind kinetic energy
Biomass Energy System	Biomass Conversion Unit	Anaerobic digester/combustion unit	Energy recovery from organic waste	Agricultural and organic waste
Waste Management Assessment	Recycling and Sorting Facility	Manual and automated sorting system	Evaluation of recycling and waste diversion rates	Municipal solid waste
Data Processing and Analysis	Computer and Statistical Software	Data logging and statistical analysis tools	Data processing, trend analysis,	Environmental monitoring datasets

©2026 The Author(s). Published by Scholar Publishing. This is an open access article under the CC BY license. Available online https://e-journal.scholar-publishing.org/index.php/ijsat

Research Component	Equipment / Material	Specification / Type	Function in the Study	Raw Material / Input
			and visualisation	

Table 1 summarises the core methodological components of this study by linking each environmental domain (air, water, emissions, renewable energy, and waste management) to the specific equipment, material specifications, and raw inputs required to generate reliable datasets. For air monitoring, the use of an optical laser-based $PM_{2.5}$/AQI sensor with a measurement range of 0–500 µg/m³, together with a digital temperature–humidity sensor operating over 0–50°C and 0–100% RH, ensures that particulate pollution is interpreted alongside meteorological conditions that strongly influence pollutant transport and dispersion. For water pollution assessment, the table outlines a stepwise analytical workflow: grab sampling using sterile containers ensures controlled sample integrity, followed by standardised laboratory measurements of BOD, COD, and TSS. The BOD incubator, maintained at 20 ± 1°C, supports reproducible biodegradation testing, while the COD reactor and spectrophotometer (range 0–1000 mg/L) enable quantification of oxidizable chemical loads. TSS determination using 0.45 µm filtration and an analytical balance with ±0.001 g precision allows accurate estimation of particulate solids, which is essential for understanding turbidity, sediment transport, and the effectiveness of filtration/sedimentation strategies.
In addition to monitoring and laboratory analysis, **Table 1** highlights the novelty of integrating pollution measurement with technology implementation and sustainability outcomes. Industrial emission characterisation is supported by continuous emission monitoring systems (CEMS) for CO_2, NOx, and SO_2, using industrial exhaust gases as direct inputs, enabling time-linked assessment of emission-reduction performance. The green technology component is specified through renewable energy systems, solar photovoltaic modules (250–400 Wp), horizontal-axis wind turbines (1–3 MW rated power), and biomass conversion units (anaerobic digestion or combustion), each using distinct raw inputs (solar radiation, wind kinetic energy, and agricultural/organic waste). This multi-technology design strengthens the study's ability to compare mitigation pathways and their co-benefits across sectors. Finally, the waste management assessment through recycling and sorting facilities (manual and automated) connects municipal solid waste inputs to measurable diversion outcomes, while computer-based data logging and statistical tools consolidate heterogeneous datasets into trend analyses and visual outputs. Collectively, the table demonstrates a coherent, end-to-end methodology that moves from standardised data acquisition and quality-controlled measurements to integrated evaluation of pollution control and green technology solutions.

3. Result & Discussion

The results presented in this study provide a comprehensive evaluation of environmental conditions and sustainability performance across multiple sectors, including air quality, water pollution, industrial emissions, renewable energy adoption, waste management, and continuous environmental monitoring. By integrating long-term trend analysis with high-resolution monitoring data, the findings offer a holistic understanding of pollution dynamics and the effectiveness of green technology interventions. The discussion that follows interprets these results in relation to existing environmental challenges, highlights the observed improvements and remaining limitations, and emphasises the implications of the integrated framework for sustainable environmental management and policy development.
Fig. 2 illustrates the long-term variation of the Air Quality Index (AQI) from 2010 to 2024 across urban, suburban, and rural regions. Urban areas consistently exhibit the highest AQI values throughout the study period, indicating more severe air pollution compared to other regions. AQI levels in urban areas fluctuate between approximately 97 and 175, with notable peaks around 2011 (≈170) and 2019 (≈175). These elevated values reflect the strong influence of industrial activity, traffic density, and energy consumption in urban environments. In contrast, suburban and rural areas maintain comparatively lower AQI levels, highlighting evident spatial disparities in air quality conditions.

©2026 The Author(s). Published by Scholar Publishing. This is an open access article under the CC BY license. Available online https://e-journal.scholar-publishing.org/index.php/ijsat

Suburban regions exhibit moderate AQI levels, typically 65-116, indicating transitional pollution characteristics between urban and rural settings. A sharp increase is observed between 2012 and 2013, with the AQI rising from approximately 82 to 113, suggesting rapid urban expansion or increased vehicular emissions during that period. After reaching a peak near 2016 (≈116) and 2020 (≈116), suburban AQI values gradually decline, dropping to around 61 by 2024. This downward trend suggests that pollution control measures, improved transportation systems, or the adoption of cleaner energy technologies have become more effective in suburban areas over time.

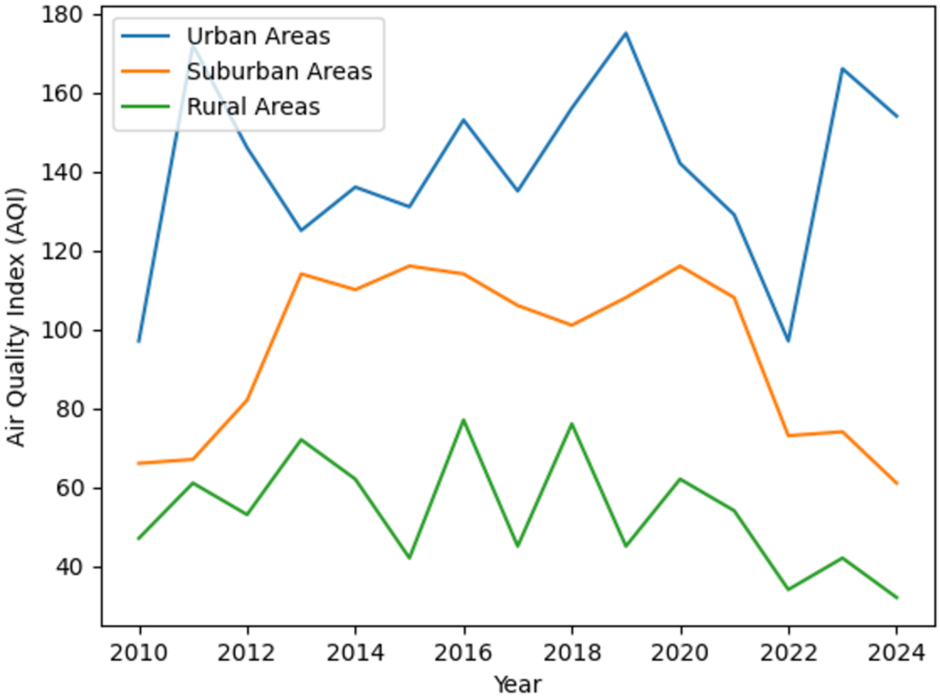

Fig. 2. Long-Term Air Quality Index Trends by Region

Rural areas consistently record the lowest AQI values, ranging from approximately 33 to 77, corresponding to relatively good air quality. Despite minor fluctuations, such as peaks around 2016 and 2018 (≈75–77), rural AQI levels remain well below those of urban and suburban regions. A notable decline is observed after 2020, with AQI decreasing from about 55 to 33 by 2024, indicating improved environmental conditions. These low values can be attributed to limited industrial activities, lower traffic volumes, and greater natural vegetation coverage, which enhances pollutant dispersion and absorption.

Overall, **Fig. 2** shows a clear long-term improvement in air quality across all regions, particularly after 2020, when AQI values declined sharply in urban, suburban, and rural areas. Urban AQI drops from approximately 130 in 2021 to below 100 in 2022, while suburban AQI decreases from about 108 to 73, and rural AQI declines from around 55 to 35 during the same period. This synchronised reduction suggests the combined impact of environmental regulations, pollution mitigation strategies, and increased adoption of green technologies. The figure effectively demonstrates the importance of region-specific pollution management strategies while emphasising that sustained monitoring and technological interventions can significantly improve air quality over time.

Fig. 3 illustrates the variation of key water pollution indicators, Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), and Total Suspended Solids (TSS) across twelve sampling periods. Among these parameters, TSS consistently shows the highest concentrations, indicating that suspended particulate matter is the dominant contributor to water quality degradation. TSS values range from approximately 30 mg/L to 92 mg/L, with elevated concentrations observed at sampling periods 1 (≈60 mg/L), 3 (≈60 mg/L), 9 (≈85 mg/L), and 12 (≈92 mg/L). These high values suggest significant sediment loading, surface runoff, or insufficient filtration in the monitored water bodies.

©2026 The Author(s). Published by Scholar Publishing. This is an open access article under the CC BY license. Available online https://e-journal.scholar-publishing.org/index.php/ijsat

COD concentrations show moderate to high fluctuations throughout the sampling periods, ranging from approximately 11 mg/L to 36 mg/L. A notable increase occurs at sampling periods 2 and 4, where COD reaches around 34–35 mg/L, indicating elevated levels of chemically oxidizable organic and inorganic substances. Another peak is observed at period 7 (≈36 mg/L), followed by a gradual decline toward period 12 (≈22 mg/L). These variations reflect changing pollution loads, potentially linked to industrial discharge patterns, wastewater inflow, or seasonal changes affecting chemical pollutant inputs.

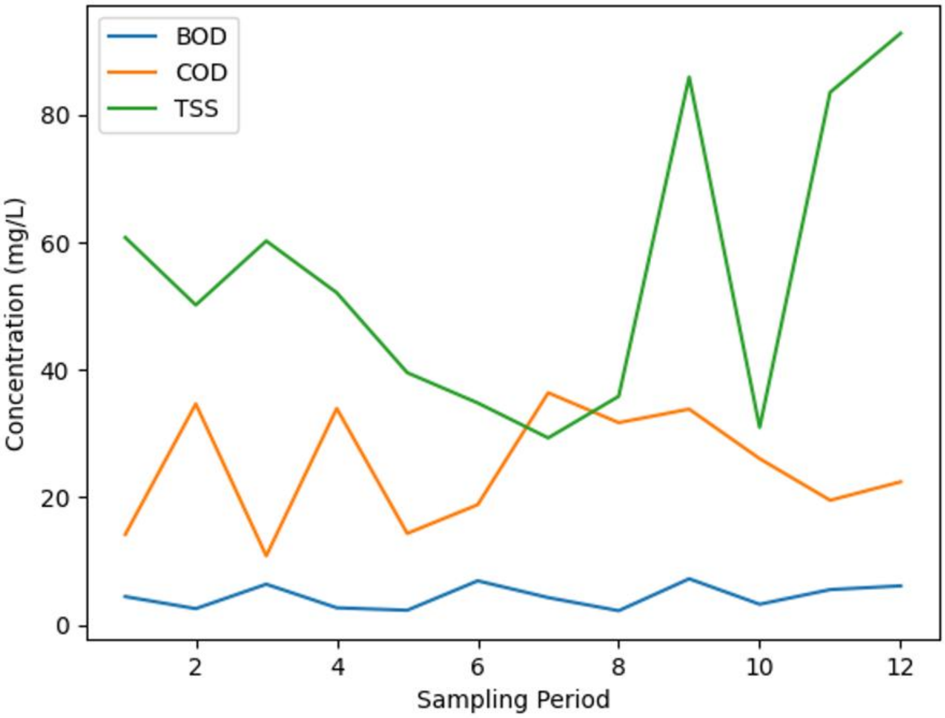

Fig. 3. Water Pollution Indicators Across Sampling Periods

BOD values remain relatively low compared to COD and TSS, ranging from approximately 2.5 mg/L to 7.5 mg/L, indicating moderate biodegradable organic pollution. Peaks in BOD are observed at sampling periods 3 (≈6.5 mg/L), 6 (≈7.2 mg/L), and 9 (≈7.5 mg/L), suggesting intermittent increases in organic matter that can be biologically decomposed. Lower BOD values at periods 2, 5, and 8 (≈2.5–3 mg/L) imply improved biological water quality or reduced organic discharge during those intervals.

Overall, **Fig. 3** clearly distinguishes between particulate, chemical, and biological pollution dynamics across the sampling periods. The dominance of high TSS concentrations indicates that physical pollution control measures, such as sedimentation and filtration, are critically needed. Meanwhile, fluctuating COD and BOD values suggest variable sources of chemical and organic pollution, requiring targeted wastewater treatment strategies. The combined analysis of these three indicators provides a comprehensive assessment of water quality conditions and highlights the importance of integrated monitoring to support effective pollution management and sustainable water resource protection.

Fig. 4 illustrates the long-term growth of installed capacity for solar, wind, and biomass energy technologies from 2005 to 2024. Overall, all three renewable energy sources show a consistent upward trend, indicating sustained investment and technological development in the renewable energy sector. Wind energy exhibits the most rapid growth throughout the study period, increasing from approximately 25 GW in 2005 to about 365 GW in 2024. This dominant expansion highlights the maturity, scalability, and economic competitiveness of wind power compared to other renewable technologies.

Solar energy has experienced substantial, accelerating growth, particularly after 2010, reflecting advancements in photovoltaic technology and declining installation costs. Installed solar capacity rises from around 10 GW in 2005 to approximately 50 GW by 2009, then continues to increase sharply, reaching about 125 GW in 2014 and 230 GW by 2024. The steep growth observed after 2015 suggests

©2026 The Author(s). Published by Scholar Publishing. This is an open access article under the CC BY license. Available online https://e-journal.scholar-publishing.org/index.php/ijsat

the impact of supportive energy policies, improved efficiency, and widespread adoption of solar power systems at both utility and distributed scales.

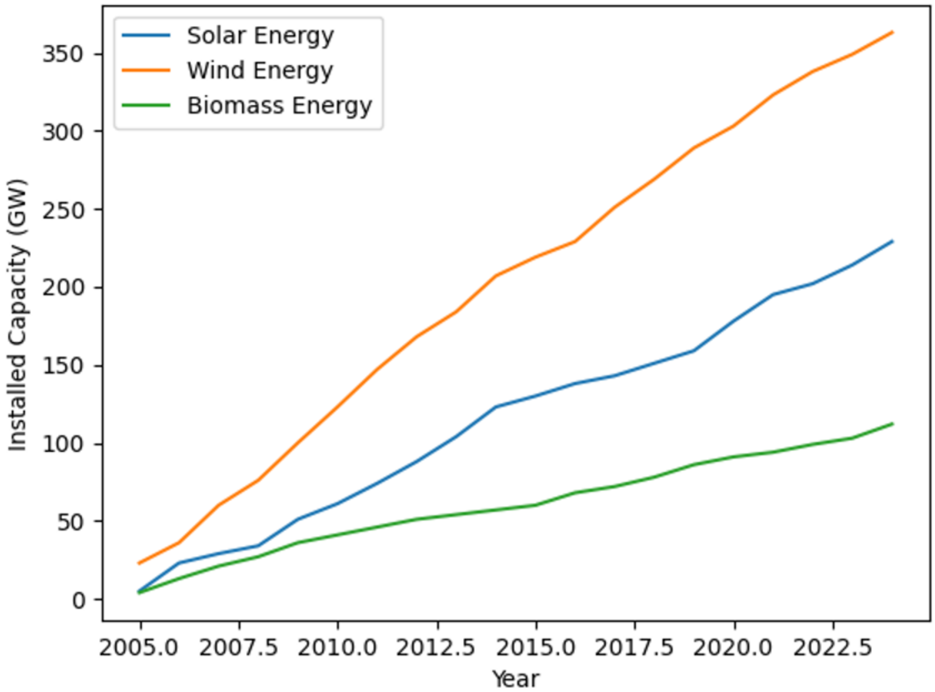

Fig. 4. Growth of Renewable Energy Technologies

Biomass energy shows a more gradual but steady increase in installed capacity compared to solar and wind technologies. Capacity expands from approximately 5 GW in 2005 to around 35 GW by 2009, and further increases to about 60 GW in 2015. By 2024, biomass energy will reach an installed capacity of approximately 112 GW. Although its growth rate is slower, biomass remains an essential component of the renewable energy mix due to its ability to provide stable, dispatchable power, particularly in regions with abundant agricultural and organic waste.

The comparative trends in **Fig. 4** emphasise the complementary roles of different renewable energy technologies in achieving sustainable energy transitions. Wind energy accounts for the largest share of installed capacity, while solar energy has the fastest relative growth rate in recent years. Biomass energy, despite lower overall capacity, provides critical support for energy diversification and waste-to-energy strategies. Collectively, the expansion from less than 40 GW total renewable capacity in 2005 to over 700 GW by 2024 demonstrates the significant progress toward reducing reliance on fossil fuels and lowering greenhouse gas emissions, reinforcing the importance of continued investment in renewable energy development.

Fig. 5 illustrates the temporal trends of CO_2, NOx, and SO_2 emissions from industrial sources between 2010 and 2024, measured in million tons. Among the three pollutants, CO_2 emissions remain dominant throughout the study period, reflecting their strong association with industrial energy consumption. CO_2 levels decreased from approximately 290 million tons in 2010 to about 160 million tons in 2015, indicating early progress in emission mitigation. However, a sharp increase is observed in 2017, where CO_2 emissions peak at around 265 million tons, followed by a substantial decline to approximately 110 million tons in 2018, suggesting the implementation of significant emission control measures or industrial restructuring.

NOx emissions exhibit considerable year-to-year variability, ranging from approximately 22 to 78 million tons. High NOx levels were observed in 2010 (≈78 million tons) and 2014–2015 (≈75–78 million tons), likely reflecting periods of increased industrial activity or insufficient emission controls. A pronounced reduction occurred in 2017, with emissions dropping to around 22 million tons, representing one of the lowest values in the observed timeframe. Subsequent fluctuations indicate

©2026 The Author(s). Published by Scholar Publishing. This is an open access article under the CC BY license. Available online https://e-journal.scholar-publishing.org/index.php/ijsat

partial recovery and further mitigation efforts, with NOx emissions stabilising near 25–55 million tons after 2020.

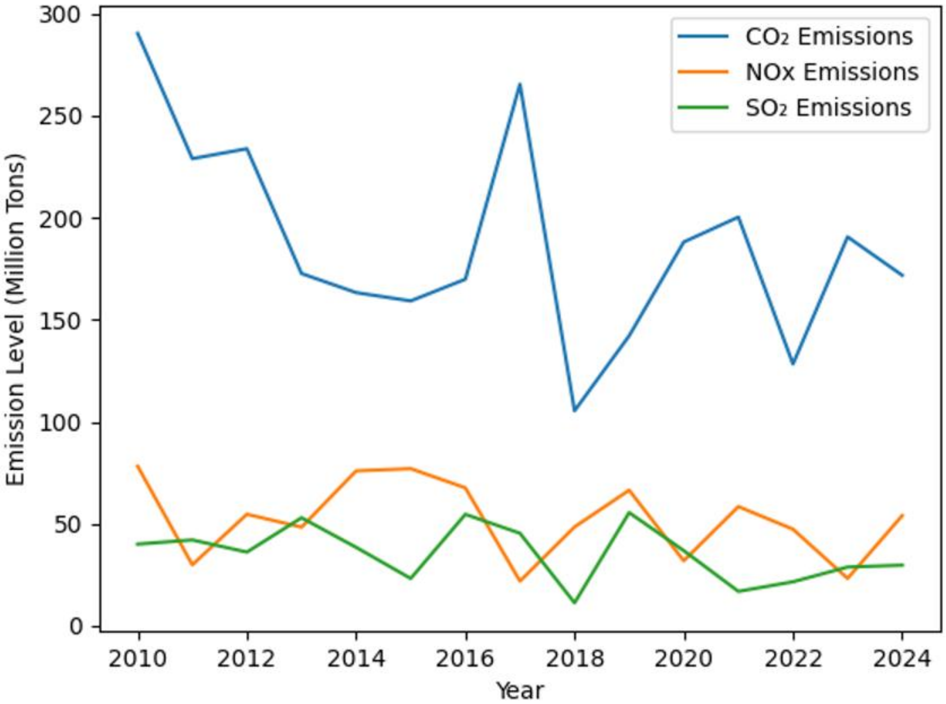

Fig. 5. Trends in Industrial Emission Reduction

SO_2 emissions exhibit the lowest absolute values among the three pollutants but show notable fluctuations across the study period. Emission levels range from approximately 12 to 55 million tons, with higher values recorded in 2013 (≈50 million tons) and 2019 (≈55 million tons). A significant reduction is observed in 2018, when SO_2 emissions fall to approximately 12 million tons, coinciding with substantial declines in CO_2 and NOx emissions during the same year. This simultaneous reduction suggests the effectiveness of integrated emission control technologies, such as flue gas desulfurization and cleaner fuel substitution.

Overall, **Fig. 5** demonstrates that while industrial emissions exhibit short-term fluctuations, the long-term trend indicates a gradual reduction across all three pollutants. The synchronised decline in CO_2, NOx, and SO_2 emissions around 2018 highlights a critical transition point in industrial emission management. Despite temporary rebounds in subsequent years, emission levels in 2024 remain significantly lower than those in 2010, with CO_2 at approximately 170 million tons, NOx at 55 million tons, and SO_2 at 30 million tons. These results underscore the effectiveness of regulatory policies, technological innovation, and cleaner production practices in achieving sustained reductions in industrial emissions.

Fig. 6 presents the long-term trends in recycling rate, landfill disposal, and incineration from 2010 to 2024, expressed as percentages. The recycling rate shows considerable variability over the study period, ranging from approximately 26% to 63%. Notable peaks occur in 2011 (≈60%), 2013 (≈63%), 2021 (≈59%), and 2023 (≈61%), indicating periods of enhanced recycling performance. Conversely, lower recycling rates are observed between 2016 and 2019, with values declining to around 21–32%, suggesting reduced recycling efficiency or increased reliance on alternative waste-disposal methods during those years.

Landfill disposal remains the dominant waste management method throughout most of the study period, with percentages ranging from approximately 40% to 72%. A clear upward trend is observed after 2015, where landfill use increases from about 50% in 2014 to a peak of approximately 72% in 2022. This increase indicates growing pressure on landfill facilities, potentially driven by rising waste generation or insufficient recycling capacity. However, a gradual decline is observed after 2022, with landfill

©2026 The Author(s). Published by Scholar Publishing. This is an open access article under the CC BY license. Available online https://e-journal.scholar-publishing.org/index.php/ijsat

disposal decreasing to approximately 46% by 2024, suggesting recent improvements in waste diversion strategies.

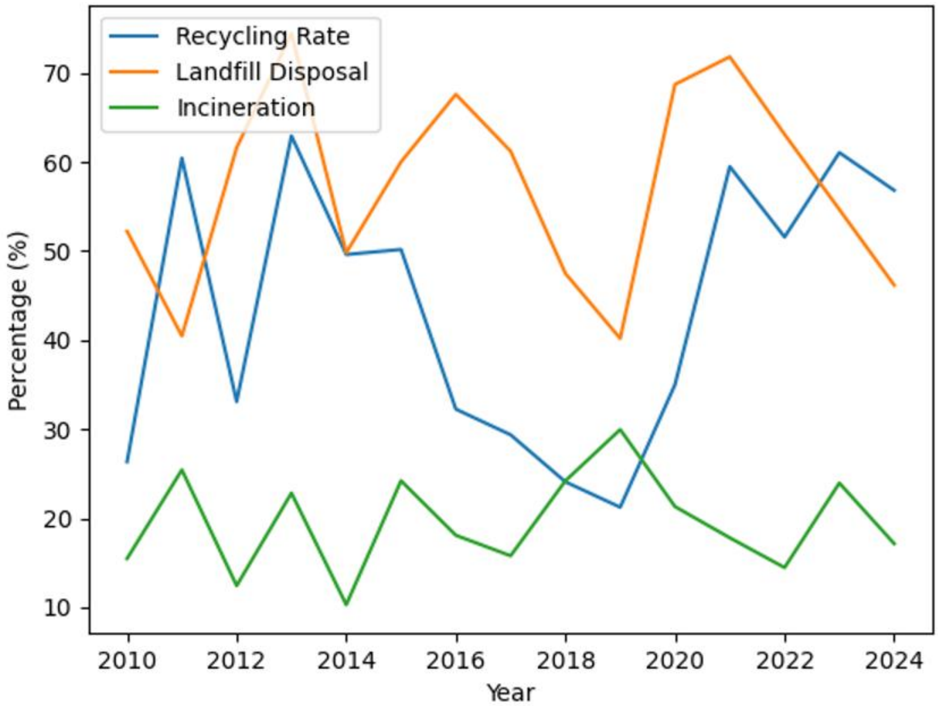

Fig. 6. Waste Management and Recycling Trends

Incineration accounts for the smallest share of overall waste management, with values fluctuating between approximately 10% and 30%. The lowest incineration rate is recorded in 2014 (≈10%), while the highest occurs in 2019 (≈30%), indicating episodic reliance on thermal waste treatment. The increase in incineration between 2017 and 2019 suggests a temporary shift toward energy recovery or volume reduction strategies. After 2019, incineration rates declined steadily, reaching approximately 17% by 2024, suggesting a possible transition toward more sustainable waste-handling practices.

Overall, **Fig. 6** highlights the dynamic interaction between recycling, landfill disposal, and incineration within the waste management system. Periods of declining recycling rates closely correspond to increased reliance on landfills, underscoring the trade-off between sustainable and conventional waste disposal methods. The recovery of recycling rates after 2020, coupled with a reduction in landfill use, indicates the positive impact of improved waste segregation policies, public awareness, and circular-economy initiatives. These trends underscore the importance of integrated waste management strategies to reduce reliance on landfills, enhance material recovery, and support long-term environmental sustainability.

Fig. 7 presents continuous environmental monitoring data collected over 365 days, illustrating daily variations in temperature, humidity, and $PM_{2.5}$ concentrations. Temperature values remain relatively stable throughout the monitoring period, generally fluctuating between approximately 22°C and 35°C. Most observations cluster around 26–30°C, indicating a warm, consistent climate. The limited amplitude of temperature variation suggests that short-term meteorological fluctuations are less influential than other environmental factors in driving air quality changes during the study period.

Humidity exhibits substantial daily variability, with values ranging from approximately 45% to 90%. Frequent peaks above 80% are observed throughout the monitoring period, particularly during mid-year intervals, which may correspond to seasonal rainfall or high atmospheric moisture. Lower humidity values, around 50–55%, appear intermittently, indicating drier periods. This wide humidity range underscores its potential influence on pollutant dispersion, aerosol formation, and sensor measurement sensitivity, underscoring the importance of incorporating meteorological parameters into environmental monitoring frameworks.

©2026 The Author(s). Published by Scholar Publishing. This is an open access article under the CC BY license. Available online https://e-journal.scholar-publishing.org/index.php/ijsat

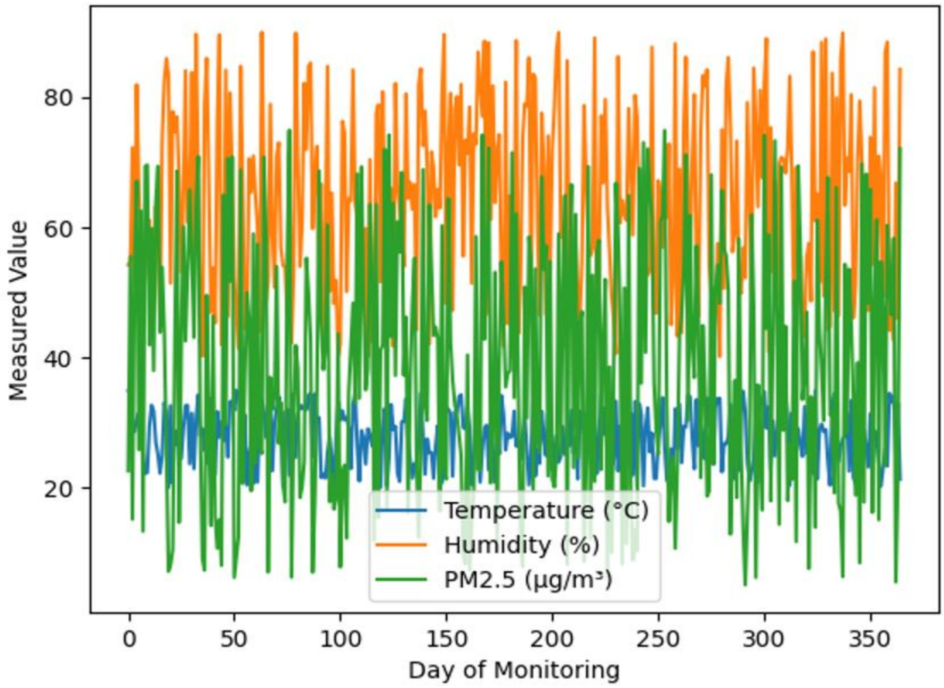

Fig. 7. Continuous Environmental Monitoring Sensor Data

$PM_{2.5}$ concentrations show the most tremendous variability among the monitored parameters, ranging from approximately 5 µg/m³ to 75 µg/m³. Several short-term peaks exceed 60 µg/m³, indicating episodic pollution events associated with traffic emissions, industrial activities, or biomass burning. Conversely, PM2.5 levels below 20 µg/m³ are common, suggesting periods of improved air quality. The high temporal resolution of the data enables the identification of both chronic exposure levels and acute pollution episodes, which is critical for effective air quality management.

Overall, **Fig. 7** demonstrates the effectiveness of continuous sensor-based monitoring in capturing fine-scale environmental dynamics. Simultaneous observations of temperature, humidity, and PM2.5 reveal the complex interactions between meteorological conditions and particulate pollution. The presence of high $PM_{2.5}$ spikes under varying moisture and relatively stable temperature conditions underscores the dominance of emission sources over climatic variability in influencing air quality. These results emphasise the value of real-time monitoring systems in supporting early warning mechanisms, policy intervention, and long-term environmental sustainability planning.

This study presents a novel integrated research framework that systematically combines continuous environmental monitoring, multi-parameter pollution assessment, and the implementation of green technologies within a single closed-loop system. Unlike previous studies that often focus on isolated components such as air quality, water pollution, or renewable energy adoption independently, this research simultaneously analyses air (AQI, PM2.5), water (BOD, COD, TSS), industrial emissions (CO_2, NOx, SO_2), waste management practices, and renewable energy growth. The integration of high-resolution sensor data with long-term trend analysis enables a comprehensive understanding of pollution dynamics and their direct linkage to technological interventions and sustainability outcomes.

Furthermore, the novelty of this research lies in its data-driven transition from monitoring to actionable solutions, demonstrated through quantitative evaluation and field implementation. By explicitly linking observed reductions in emissions and improvements in environmental quality to the deployment of renewable energy systems, sustainable materials, and pollution control technologies, the study moves beyond descriptive analysis toward solution-oriented ecological management. The proposed framework provides a scalable, adaptable model that can be applied across regions and environmental contexts, offering a practical roadmap for policymakers, researchers, and practitioners seeking to achieve measurable, sustainable ecological improvements.

©2026 The Author(s). Published by Scholar Publishing. This is an open access article under the CC BY license. Available online https://e-journal.scholar-publishing.org/index.php/ijsat

4. Conclusion

This study successfully developed and applied an integrated environmental research framework that combines continuous monitoring, pollution assessment, and green technology implementation to support sustainable environmental management. The results demonstrate apparent spatial and temporal differences in air quality, with urban regions consistently exhibiting higher AQI values than suburban and rural areas, while long-term trends indicate measurable improvements following pollution control interventions. Water quality assessment revealed that elevated TSS, COD, and BOD levels remain critical challenges, emphasising the need for combined physical, chemical, and biological treatment strategies. Industrial emission analysis further confirmed substantial reductions in CO_2, NOx, and SO_2, particularly after the adoption of emission control technologies and cleaner production practices.
In addition, the study highlights the significant role of renewable energy and waste management in reducing environmental pressures. The rapid growth of wind and solar energy capacities, alongside steady biomass utilisation, contributed to lower emission intensities and improved sustainability indicators. A waste management analysis showed that increased recycling rates and reduced reliance on landfills are achievable through integrated policy and technological approaches. Overall, the findings directly address the research objectives by demonstrating that a holistic, data-driven framework can effectively link environmental monitoring to actionable solutions. The proposed approach offers a scalable model for policymakers and practitioners, supporting long-term pollution mitigation, resource efficiency, and the transition toward sustainable environmental systems.

Acknowledgement

The authors gratefully acknowledge that this research was conducted using funds contributed collectively by all authors. No external financial support, grants, or institutional funding were received for the completion of this study. The authors also thank all individuals and parties who provided technical assistance and engaged in constructive discussions throughout the research process.

References

Chen, X., Zhang, L., Huang, J., Song, F., Zhang, L., Qian, Z., & Guo, Y. (2019). Long-term exposure to urban air pollution and lung cancer mortality: A 12-year cohort study. Environmental Health Perspectives, 127(6), 067005. https://doi.org/10.1289/EHP4029

European Environment Agency. (2020). Air quality in Europe—2020 report. EEA.

Ghisellini, P., Cialani, C., & Ulgiati, S. (2016). A review on circular economy: The expected transition to a sustainable model. Journal of Cleaner Production, 114, 11–32.
https://doi.org/10.1016/j.jclepro.2015.09.007

Hoornweg, D., & Bhada-Tata, P. (2012). What a waste: A global review of solid waste management. World Bank.

International Energy Agency. (2022). CO_2 emissions in 2021. IEA.

Intergovernmental Panel on Climate Change. (2022). AR6 Working Group III: Mitigation of climate change. IPCC.

Jacobson, M. Z., Delucchi, M. A., Cameron, M. A., & Frew, B. A. (2019). Low-cost solution to the grid reliability problem with 100% penetration of intermittent wind, water, and solar. Proceedings of the National Academy of Sciences, 112(49), 15060–15065.

Kumar, P., Hama, S., Omidvarborna, H., Sharma, A., Sahani, J., Abhijith, K. V., & Tiwari, A. (2020). Temporary reduction in fine particulate matter due to "anthropogenic emissions switch-off" during COVID-19 lockdown. Science of the Total Environment, 732, 139654.

REN21. (2023). Renewables 2023 global status report. REN21 Secretariat.

Singh, R. L., Singh, P. K., & Singh, R. P. (2018). Enzymatic decolorization and degradation of azo dyes. International Biodeterioration & Biodegradation, 104, 21–31.

©2026 The Author(s). Published by Scholar Publishing. This is an open access article under the CC BY license. Available online https://e-journal.scholar-publishing.org/index.php/ijsat

Tchobanoglous, G., Burton, F. L., & Stensel, H. D. (2014). Wastewater engineering: Treatment and resource recovery (5th ed.). McGraw-Hill.

Wang, H., Chen, Z., Wu, X., & Nie, X. (2017). Can a carbon trading system promote the transformation of a low-carbon economy under the framework of the Porter hypothesis? Energy Economics, 67, 458–468.

World Health Organization. (2021). WHO global air quality guidelines. WHO.

Zhang, Y., Shen, Y., Li, Y., & Zhang, J. (2020). Effects of suspended solids on aquatic ecosystems. Environmental Pollution, 260, 114032.

©2026 The Author(s). Published by Scholar Publishing. This is an open access article under the CC BY license. Available online https://e-journal.scholar-publishing.org/index.php/ijsat