Chapter 18

Advanced Materials, Artificial Intelligence, and Sustainable Technologies for Energy and Environmental Engineering
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Artificial Intelligence for Environmental Monitoring and Pollution Management

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ABSTRACT

Artificial intelligence (AI) has emerged as a promising tool in environmental monitoring and pollution control, providing new possibilities for real-time analysis, predictive modeling, and autonomous decision-making. These technologies are surveyed in a chapter on AI for various environmental fields, including air quality monitoring, water pollution control, soil contamination detection, and emerging application areas such as carbon dioxide tracking or biodiversity conservation. We review in-depth machine learning algorithms, deep learning models, and ensemble methods as we discuss AI technologies for environmental stewardship. The chapter comprises four comprehensive bibliographic tables that summarize the key results for MDPI papers, along with their corresponding performance graphs at this level. This analysis reveals that AI models have had a significant influence on shaping research. Critical issues, such as data quality, computational inefficiency, model interpretation, and ethical implications, are thoroughly discussed, along with policy suggestions and promising research directions.

Keywords: Artificial Intelligence; Environmental Monitoring; Pollution Control; Machine Learning (ML); Deep Learning (DL); IoT Sensors; Real-time Monitoring; Prediction Analysis.

INTRODUCTION

Degradation and contamination of the environment have emerged as a serious global issue that affects human health, the functioning of interconnected systems, and sustainable development. Conventional monitoring method. All of China's current water quality standards for small rivers consider the long-term average and prompt concentration, with a time delay of up to 20 h for some fixed-point provinces.(1,2,3,4,5,6,7,8) These limitations affect the ability to respond quickly in a contamination incident, as well as to monitor an environment geographically. Urbanization, industrialization, and transportation have contributed to a rise in pollution out of all proportion - especially in the developing world, where nine of the top ten most polluted cities are located.(2,9,10,11,12,13,14,15) Conventional environmental monitoring approaches have a limited capability by nature, as they involve human effort and resources to establish, manage, and collect real-time information for proactive resource management.(3,16,17,18,19,20,21,22,23)

AI for pollution monitoring

The AI technology possesses revolutionary potential in Environmental monitoring and pollution control, along with Super processing of large databases, which is enormously fast at recognizing and analyzing complex patterns in any application, enabling the search for solutions of enormous proportions faster than previously.(4,24,25,26,27,28,29) Artificial intelligence (AI) functions, such as machine learning (ML), deep learning (DL), advanced analytical algorithms, and more, can be utilized to enable real-time detection, prediction, and autonomous response capabilities that operate transparently across various environmental domains.(5,30,31,32,33,34,35) AI (as well as IoT, and other technologies) can integrate satellite remote sensing data, Internet of Things (IoT) sensor data, or even drone observation to establish multi-scale monitoring networks that provide early detection of pollution in near real-time, as well as in situ forecasting of environmental parameters with high accuracy.(6,36,37,38,39,40,41,42) This chapter categorizes a range of AI environmental monitoring/pollution control technologies, encompassing both conventional and advanced systems. It then examines the practicality of these two traits of deep learning in real-world scenarios, state-of-the-art evaluation methods, and the associated challenges.(43,44,45,46,47,48,49,50) By critically evaluating the most recent AI research and applications in various domains, this chapter highlights that these new machine-learning systems surpass traditional precursors in detection accuracy (80e(95 %), communication delay (24 hours e0 1 hour), cost (~0,4X expenses), and spatial extent (up to 5X locations).(7,51,52,53,54,55,56,57) Drawing on evidence from over 30 peer-reviewed studies across various environmental domains,(58,59,60,61,62,63,64) it provides researchers, policymakers, and experts with a comprehensive understanding of how AI is poised to be the transformational engine shaping ecological well-being and sustainability. An Introduction to Elementary Image Processing and Analysis with Application to Environmental Monitoring.(65,66,67,68,69) An illegal access exception to metadata during deep learning for environmental monitoring.(70,71,72,73)

Table 1. Summary of studies on AI-assisted environmental monitoring

Title	Year	Focus Area	Key Technology	Performance Metrics	Author/Source
AI-Driven Greenhouse Gas Monitoring: Enhancing Accuracy and Efficiency	2025	GHG Monitoring	Random Forest, SVM, CNN, LSTM	Detection accuracy 95 %, RÂ²=0,89	Hasan et al.(4)
Prediction of PM2,5 Concentration Based on CNN-LSTM Deep Learning	2024	Air Quality Prediction	CNN-LSTM Deep Learning	RÂ²=0,91, RMSE=8,216 Âµg/mÂ³	Bai et al.(30)
Air Quality Index Forecast in Beijing Based on CNN-LSTM	2022	Air Quality Forecasting	CNN-LSTM Model	MAE reduced by 43 %, RMSE by 53 %	Zhang et al.(33)
Deep Learning for Prediction of Air Quality Response to Emission Changes	2020	Emission Response	Deep CNN with RSM	CNN-based DeepRSM reliable	Xing et al.(47)
IoT-Based Real-Time Water Quality Monitoring System	2024	Water Quality	IoT Sensors, PLC, SCADA	Error margin 0,1-0,2	Forhad et al.(52)
Air Pollution Prediction with Machine Learning: A Case Study of India	2022	AQI Prediction	XGBoost, Random Forest, SVM	XGBoost highest accuracy	Kumar et al.(2)
Artificial Intelligence-Assisted Air Quality Monitoring for Smart Cities	2023	Smart Cities	Feature-Optimized LSTM	Best RÂ² for AQI prediction	Neo et al.(43)
Air Quality Prediction and Control Systems Using Machine Learning	2024	Pollution Control	ANFIS, MLP, Random Forest	RÂ²=0,999 (Winter 2020)	Mottahedin et al.(57)

A Hybrid Deep Learning Air Pollution Prediction Approach	2025	Hybrid Models	Deep Learning Hybrid	Complex spatio-temporal handling	Chen et al.[27]
Real-Time IoT-Powered AI System for Environmental Monitoring	2024	Comprehensive Monitoring	IoT with Machine Learning	94 % prediction accuracy	Ramadan et al.
Revolutionizing Water Quality Monitoring with AI	2025	Water Quality Systems	ANFIS, DNN, Satellite Integration	60 % cost reduction	Al-Khafaji et al.[1]
The Role of Artificial Intelligence in Environmental Monitoring	2025	Environmental Monitoring	Remote Sensing, AI	Real-time source identification	IK Press[3]
An Embedded Machine Learning System for Air Quality Monitoring	2025	Low-Cost Sensors	ORCS-ASVM	Improved accuracy over traditional	AIMS Press[9]
AI in Combating Deforestation	2023	Deforestation Detection	Satellite Image Analysis	Near real-time detection	Omdena[69]
Bridging Adaptive Management and Reinforcement Learning	2023	Adaptive Management	Reinforcement Learning	Model-free deep RL	Chapman et al.[6]
Using AI and GIS for Real-Time Forest Monitoring	2025	Forest Monitoring	AI, GIS, Satellite Imagery	Temporal dense monitoring	Geowgs84.ai[74]
Real-Time Water Quality Monitoring Using AI-Enabled Sensors	2024	Water Quality Detection	AI-Enabled Sensors	26 citations	Durgun et al.

Conceptual framework and technology foundation

Environmental artificial intelligence integrates various scientific and technological inventions to build intelligent systems capable of monitoring the environment independently.[8] Its data collection, analytics, and decision support capabilities are built on three main components: infrastructure for data capture, technology for processing it, and systems for informed decision-making. DSMSA sources include distributed sensor networks, satellite platforms, UAVs (Unmanned Aerial Vehicles), UGVs (Unmanned Ground Vehicles), and ground stations, which observe multi-dimensional environmental phenomena over extended time series and globally.[9] The sensor layer utilizes multiple types of sensors, each suited for various mission profiles. Multi-pollutant monitors measure gaseous pollutants (carbon monoxide (CO), nitrogen dioxide (NO2), sulfur dioxide (SO2), ozone (O3), ammonia, NH3) and particle sensors for fine particles (PM2,5) and coarse particles (PM10).[10] The water quality sensors monitor key parameters, including pH, dissolved oxygen (DO), turbidity, conductivity, total dissolved solids (TDS), and other contaminants. The sensors are interfaced with microcontroller hardware (Arduino, Pi, ESP32) for local or edge computation of data.[11] Wireless communication infrastructure supports heavy data traffic delivery from sensor nodes deployed in a location to other places through different wireless paths, such as Long Range Wide Area Network (LoRaWAN) for long-range but less energy-efficient connectivity, 5G for real-time and high bandwidth data transmission, Wi-Fi for local area network, and cellular network (LTE) providing services in mobile platform.[12] This hybrid architecture ensures diversity, scalability, and coverage in various scenarios, ranging from rural to urban areas.[13] The analytical processing layer comprises cloud servers (e.g., AWS, Google Cloud, Azure), which preprocess raw sensor readings to extract features for model-based analysis.[14] Edge computing approaches split processing between mobile devices and cloud services to minimize latency, bandwidth requirements, and computational overhead exerted on centralized infrastructures.[15]

Machine Learning for Environmental Data

Then, data-driven methods for environmental monitoring can generally be categorized into three groups: 1) supervised learning based analyses; 2) unsupervised learning-based analyses; and 3) reinforcement-learning-based analyses, considering the specific analysis purpose. Supervised learning approaches utilize labeled historical data to train a predictive model, which can then predict pollution concentrations, contamination events, or environmental quality indexes.[16] Support vector machines (SVMs) are effective methods for analyzing multidimensional ecological data, and the nonlinear correlation of diverse pollutants or meteorological factors can be readily expressed by SVMs.[17] Interpretable models (e.g., DTree/RForest ensemble) generalize well across different environmental conditions.[18] Among them, the eXtreme Gradient Boosting (XGBoost) is reported as one of the most popular learners, leveraging three learning algorithms, an advanced machine learning model, and an ensemble method based on the iterative improvement of weak learners.[8] It is one of the most effective approaches to achieve high accuracy prediction (yielding 97 % accuracy compared to alternative algorithms).[19] Although simple, the Gaussian naive Bayes method emerged as a very competitive approach, particularly in specific AQ scenarios where the feature independence assumption holds.[20]

Unsupervised learning techniques are designed to identify hidden structures, outliers, and anomalous patterns within unlabeled environmental data. K-means clustering can divide the air quality monitoring data into distinct clusters, making the original complex information on pollution and variation clearer.[21] Techniques, such as Principal Component Analysis (PCA), can be used to address the issue of dimensionality reduction by converting high-dimensional meteorological data into principal components that are more interpretable and reflect the primary pollution sources/determinants.[22] The variability of temporal and spatial patterns of pollutants is not reported, except for duration times through HR. Some pollution events or seasonal variations can be identified.[23] Adaptive environmental management, which has recently been recognized as an attractive paradigm built on reinforcement learning,[19] enables intelligent agents to learn from experience in an environment without being explicitly told what is right or wrong.[24] RL techniques have also been applied to dynamic sensor placement,[25] where robots learn to place sensors to achieve the optimal trade-off between the information gained and the pollution detected. Robotized systems (multiple robots, learning-based algorithms) have been developed to map pollution sources in contaminated environments, especially on dynamic contamination fields.[26]

Table 2. Performance of different algorithms in predicting air pollutants

Model/Method	Application	Accuracy/ Performance	Key References
Random Forest (RF)	AQI prediction, PM2,5/PM10 forecasting	98,2 % accuracy, RÂ²=0,9998	Ravindiran et al.; Ameer et al.
ANFIS (Adaptive Neuro-Fuzzy Inference System)	Seasonal air quality prediction, pollutant concentration modeling	RÂ²=0,999, RMSE=0,0274	Mottahedin et al.[57]
Support Vector Machines (SVM)	Classification of air pollutants, anomaly detection	93 % average accuracy	Veljanovska & Dimoski
Neural Networks (ANN, MLP)	PM prediction, CO2 forecasting, multi-pollutant analysis	87 % correlation coefficient	Maleki et al.; Taheri & Razban

Convolutional Neural Networks (CNN)	Satellite imagery analysis, spatial pollution mapping	95 % detection accuracy	Bashardoost et al.
Long Short-Term Memory (LSTM)	Time-series forecasting, temporal pattern recognition	High temporal accuracy for sequential data	Shahana et al.
Gradient Boosting & XGBoost	High-accuracy AQI prediction, feature importance analysis	RÂ^2=0,9936, superior performance	Ravindiran et al.
Ensemble Methods (Stacking)	Combining multiple base learners for improved accuracy	RÂ^2>0,99, reduced error rates	Air Quality Prediction
Deep Belief Networks (DBN)	Deep feature extraction from air quality data	Improved feature learning	Air Quality Prediction
CatBoost	Categorical variable handling, robust prediction	RÂ^2=0,9998, low RMSE	Ravindiran et al.

DLA4HD: Deep learning architectures for high-dimensional environmental data

Deep learning methods are particularly effective in modeling nonlinear and complex relationships, as well as extracting hierarchical patterns from environmental data streams.[27] CNNs show great promise in analyzing spatial ecological data, such as satellite images, drone videos, and gridded sensor networks.[28] CNNs using convolutional filters are models capable of learning multiscale spatial features, which allows the identification of pollution patterns at various geographical scales, such as local and continental.[29] In addition, the LSTMs explicitly take account of temporal ordering in environmental time series data by maintaining a memory of past observations through gates that update hidden states iteratively.[30] The LSTM model was employed in prediction studies for air quality indices, considering seasonality and meteorological factors associated with pollution.[31] BiLSTM processes the sequence of environment \emph{forward} and \emph{backward} to derive forward--backward temporal relations that can enhance prediction performance.[32] Hybrid deep learning models, which combine CNNs and LSTMs, leverage the advantages of both spatial feature extraction using CNNs and modeling temporal dynamics with LSTMs.[33] The CNN-LSTM architecture processes environmental data through a body-sequence stage, in which the CNN layer extracts important spatial patterns from sensor field (or satellite) observations at different locations, and the LSTM layer models the temporal changes of these patterns.[34] CNN-LSTM models have also been shown to be more accurate than others for forecasting air quality, with an R^2 of 0,91 and an RMSE of 8,216 μg/m^3 of PM2,5 modeled.[16] 5 concentration prediction (R^2 = 0,89, RMSE = 9,41), which is significantly better than either the separate CNN (R^2 = 0,85, RMSE = 11,356) or LSTM (R^2 = 0,83, RMSE = 14,367).[35]

Table 3. AI technologies and models for soil pollution detection and prediction

Technology/Model	Application	Performance Metrics	Advantages	Key Studies
Graph Neural Networks (MSA-GNN-HMP)	Soil heavy metal prediction (Cd, Pb, Ni, Cr)	Lowest MAE & RMSE, highest RÂ^2	Multi-scale spatial feature extraction, attention mechanism	Zha et al.
Convolutional Neural Networks (CNN)	Spectral analysis for soil contamination	High accuracy in contamination detection	Image-based analysis, non-invasive	Pyo et al.; Sun et al.
Random Forest (RF)	Spatial prediction of soil quality parameters	89-95 % prediction accuracy	Handles non-linear relationships well	Li et al.

Support Vector Regression (SVR)	Heavy metal concentration estimation	Effective spatial modeling	Robust to outliers	Yang et al.
Artificial Neural Networks (ANN)	Soil quality index prediction	85-92 % accuracy range	Captures complex patterns	Pacci et al.
IoT + Edge Computing	Real-time environmental monitoring in remote areas	Low latency (<1ms), real-time capability	Distributed monitoring, fog computing integration	Baharudin et al.; Roostaei et al.
Remote Sensing + AI	Oil contamination detection, TPH/PAH quantification	95 % accuracy in contamination identification	Large-area coverage, satellite data integration	Remote Sensing Studies
E-nose + Spectroscopy	Rapid detection of chemical pollutants in soil	Rapid on-site analysis	Portable, field-deployable	Spectroscopy Research
Deep Learning (Hybrid)	Multi-sensor data fusion for pollution assessment	Enhanced multi-modal performance	Integrates multiple data sources	Chen et al.
Fuzzy PLS + BLN	Heavy metal detection in agricultural soils	Improved accuracy over traditional PLS	Handles dynamic sensing data	Chen et al.

Graph Neural Networks (GNNs) offer a novel framework for monitoring over interconnected spatial domains.(36) GNNs address the relationships between monitoring stations and environmental compartments related to multisource pollutants, capturing how pollutants are transferred through air, water, and land systems.(37) Attention mechanisms developed in a neural context51 are used to selectively weigh the computational output, resulting in increased feature interpretability and efficiency when selecting other potentially informative environmental variables and their corresponding temporal windows.(38) The problem of identifying which ecological features contribute most to pollution levels has been addressed by a class of attention module-equipped CNN-BiLSTM models.(39) In addition, such models offer learnable weights to determine which input variance most contributes to predicting pollution results.(40) The temporal-based model, trained to predict air pollution, incorporates an attention mechanism and achieves R^2 values of 0,9872 for PM2,5, demonstrating the potential of attention methods in complex environmental applications.(41)

Justification of AI in Environmental Monitoring

Monitoring and Forecasting of Air Quality 6,1.determination with which the measurements are made and known (in some cases interpolated) concentrations at sample sites. The measurement network serving as the input to the data fusion problem is predominantly composed of non-stationary sensors with inhomogeneous sensitivities that exhibit varying levels of noise.

The area of air quality monitoring is one of the most developed and explored areas where AI has been applied to environmental management, as it addresses evident public health issues associated with atmospheric pollutants.(42) Traditional approaches to air quality monitoring and assessment are typically based on a limited number of centralized monitoring stations, spaced apart from several meters to several kilometers, leading to both blind spots in the pollution coverage map and latency in detecting local pollution events.(43) Air quality monitoring systems based on AI deploy a decentralised network of sensors over cities, thereby generating high-resolution pollution maps with fine spatiotemporal granularity.[44] Machine learning methods are developed to integrate sensor readings with meteorological variables (temperature, wind speed, relative humidity, and atmospheric pressure) to predict pollutant levels at different horizons: immediate (1-6 hours), short-term (24-72 hours), long-term, seasonal, and annual.[45,46] The deep learning technique has been successfully applied in air quality forecasting. DeepRSM) The two emission perturbations and the responses of air quality predictions, such as this model, can be a very accurate predictor for both temporal variation and space-time pattern on a daily timescale, which can faithfully emulate complex CMAQ models. DeepRSM targets precursor pollutants (NOx, SO2, and ammonia) to secondary pollutants (ozone and PM2,5) by using deep convolutional models to forecast real-time air quality responses under policy choices.[47]

The published outputs of deep learning algorithms, when applied to air quality forecasting in large cities, demonstrate a better comparison with traditional statistical methods. The Beijing air quality forecast based on CNN-LSTM models has an average absolute error of 43 % and a root mean square error of 53 %, compared to the SARIMA (Seasonal Autoregressive Integrated Moving Average) model, which increases the R^2 value by 8,45 %.[48] CNN-BiLSTM Modelling for Mumbai, India considers 13 pollutants and seven meteorological factors at this level to estimate air quality index and achieves R^2: 0,91; MAE (0,45); RMSE (0,60).[49] PM2,5 and the found parameters 'g' were discovered while an optimized feature LSU model was utilized in the ASmart City Air System. This work. 5, PM10, NO2, along with weather factors including humidity and wind speed, as the major predictors to predict pollution levels.[50] These models achieve optimal R^2 for estimating multiple pollutants in large cities, suggesting that AI can predict several pollutants simultaneously by forecasting estimates for various types of contaminants. This is expected to assist overall air quality planning.[51]

Analyses of Water and Characterization of Contamination

A DS-internet of things (IoT)-based water quality monitoring system can easily overcome traditional methods by providing real-time and continuous results for multiple parameters.[52] Numerous sensor arrays are used to monitor pH, dissolved oxygen (DO), turbidity, conductivity, and other chemical pollutants in water treatment plants, factories, and municipal water supplies.[53] PLC SCADA Cloud X: A gateway between IoT and cloud II. Existing techniques are increasingly focused on developing smart, Innovative Water Systems to address issues related to growing urbanization, digital dynamics, and climate change.[47,48,49,50,51,52] It is capable of providing a minimum error margin of 0,1 and 0,2 in measurements for different parameters, which permits the prompt detection of variations in water quality and contamination events.[55] Machine learning of water quality data facilitates the detection of anomalies, such as identifying unusual patterns that may indicate pollution, sensor malfunctions, or process faults.[56] ANFIS could also produce superior results in modeling the water quality prediction (R^2 = 0,999, RMSE = 0,0274, MAE = 0,0162).[57] This breakthrough level of performance represents a fundamentally different capability for traditional statistics methods, as practical predictive maintenance can be performed and contamination dealt with proactively.[58] AI intelligent water sensing systems can lower the sampling period to around 60 %, based on strategically placed sensors calibrated by machine learning (ML) models.[59] The combination of IoT sensor networks and integration of satellite data (Landsat 8) has made it possible to map water quality in large areas where extensive field sampling was previously needed.[60] Sophisticated fusion techniques that combine different data sources may provide continuous ranging information for water quality considerations in watershed-scale management.

Smart City Air Pollution Sensing and Abatement

Advanced city deployments. The other two novel and evolutionary city-level deployments utilize AI-automated air pollution monitoring, integrated into the city structure, to create a detailed picture that was previously unavailable using traditional monitoring approaches, providing both a stationary and dynamic view of pollution in space and time.[62] By measuring the quality of air in real-time, urban planning measures can be activated. Traffic is optimized during pollution episodes to reduce congestion and pollutants. Air quality controls public transport schedules and designates clean air areas, places where vehicle access is limited due to persistent poor air quality.

AI-enabled intelligent urban air quality monitoring techniques might predict pollutant concentrations on a neighborhood scale, recognize pollution hotspots, and provide a basis for targeted actions.[64] In the Greater Chennai area of India, AI-driven air quality monitoring systems are expected to lead to the planting of over 200 000 trees by 2023, as part of a larger plan to reduce PM2,5 pollution by 2026.[65] Variational autoencoders and hybrid AI models, such as those embedded with machine learning and edge computing (e.g., adaptive SVMs controlled by one-rank cuckoo search optimization), have been utilized to enhance the accuracy of low-cost sensors.[66] The ORCS-ASVM method utilizes real-time data for SO2, NO2, and PM2,5. 5. Monitoring, gathered through Raspberry Pi edge nodes, which enables improvements in prediction accuracy and reductions in computational needs.[67] This on-device ML-based method will pave the way for reliable air monitoring at scale in resource-constrained urban environments.[68]

Forest Monitoring and Deforestation Alerts

AI-driven satellite imagery for monitoring forest cover improves deforestation detection and evaluation of forest health.[69] The AI-based satellite image analysis processes utilize multispectral and hyperspectral images taken from the Sentinel-2, Landsat 8, and other Earth observation satellites to predict changes in forest cover, albeit near real-time.[70] High-speed algorithms can be used to decode deforestation areas for swift organization of interventions and law enforcement.[71] Deep learning models trained on large-scale satellite images learn to distinguish between forest cover and degradation patterns, as well as identify illegal logging and natural disturbances.[72] Forest and non-forest classes of satellite pixels are well-discriminated by Random Forests, Support Vector Machines, and Convolutional Neural Networks.[73] Time series analysis enables the explicit detection of changes in crown density (degradation) and trends in degradation, as this gradual ecosystem transition precedes complete deforestation.[74] The combination of optical and radar satellite data with AI-based enhancement enables time-dense monitoring of forests, compensating for artifacts caused by poor cloud accessibility in optical images.[75]

Radar satellites can see through clouds, enabling continuous observations that supplement voids left by optical data. To the extent that these events are shrouded in cloud cover for extended periods, particularly in tropical regions, this is relevant.[76] This fusion approach has been used to track small-scale disturbances (e.g., illegal logging) that regrow rapidly, as they do not produce temporal aliases (i.e., the recovery of vegetation will not mask deforestation signals).[77] AI predictive models determine which areas are most likely to be deforested by 1911—the year that historical content ends—factoring in historical trends, land-use changes, population density, and infrastructure development.[78] Such predictive maps would allow for a cost-effective and pragmatic implementation, where monitoring and enforcement efforts are concentrated in high-risk areas (to facilitate efficient protection of highly vulnerable zones with limited resources).[79]

Agro-food and Marine Ecosystem, Ocean Pollution Observing

AI-driven e-marine systems completely change the way ocean observing is done by utilizing autonomous platforms, intelligent sensors, and on-site data analysis.[80] The improved presence of autonomous underwater and glider vehicles with environmental sensors thus offers continuous monitoring of water column temperature, salinity, pH, and oxygen, as well as species distributions.[81] Sophisticated imaging technologies (e.g., high-resolution cameras and sonars) are used to produce highly detailed visual imagery, which is then interpreted by machine learning algorithms to discern the species in question, monitor movements among potentially migratory communities, and identify any behavioral deviations.[82] Acoustic monitoring, aided by machine learning techniques, analyzes underwater sounds to identify and track the behavior of marine mammals, as well as to study their communication.[83] These functions are handy for managing whale populations or examining the migration routes of whales, which also have a significant influence on protecting the maritime environment.[84] Based on ocean temperature, water salinity, pH balance, and species distribution, among other factors, predictive analytics combined with marine ecosystem data are used to forecast possible changes in the aquatic environment.[85] Rapid logistical support for interventions, such as coral bleaching events or harmful algal blooms, and ecosystem stress alerts can also be essential.[86] The small spatial patterns of the environment that are invisible to the human eye can be detected by AI algorithms to forecast species migration and preserve resources.[87]

It has been demonstrated that artificial intelligence (AI)-based systems can be practically used to detect pollution in the sea, such as oil spills and plastic garbage,[88] as well as pollutants in marine environments using satellite images and distributed sensor networks—satellite-AI for oil spill detection. Satellite AI exhibits high precision in sensing oil fingerprints, slicks, and damage of a spill.[89] HAB prediction is an environmental forecasting method that combines information to predict the location and magnitude of harmful algal blooms (HABs) for public health protection.[90]

Measuring Greenhouse Gases and Tracing Emissions to Climate

The AI-based monitoring system for GHG facilitates emissions monitoring and reduces errors by pooling real-time information from various sources.[91] Machine learning algorithms and neural networks analyze satellite imaging, IoT sensors, and meteorological models to detect emission hotspots and monitor their spatiotemporal patterns.[92] The GHG monitoring methods using random forest, support vector machine (SVM), convolutional neural networks (CNNs), and long short-term memory (LSTM) are developed for a significant improvement on latency from 24 hours to 1 hour in reporting the data; spatial resolution of 30 metres to 10 metres, and accuracy from 80 % to 95 %.[93] AI systems detect and estimate emission sources that are not explicitly present in the training data, then extrapolate emission projections with an R^2 of 0,89.[94]

These developments will enable more effective regulatory action and policy for reducing climate change.[95] AI can further assist in the targeted reduction and quantification of emissions, considering their evolution over time, as well as the evaluation of climate policies.[96]

Integration Technologies and System Architecture

IoT Sensor Networks and Edge Computing 3ENSITY16 define the resources of sensors as their remaining energy. Various methods are employed to conserve computational power through sleep modes, for example, by utilizing software libraries that benefit from modern compilers or minimizing data.

In real-time environmental monitoring systems, IoT sensor networks are integrated with edge computing to process data locally before transferring it to cloud platforms.[97] This distributed approach minimizes latency, communication overhead, and computation load on centralized servers—Scanes enables local responses upon detection of an anomaly.[98]

Sensor arrays for CO, NO2, SO2, PM2,5, PM10, and O3 require an integrated preprocessing that includes feature extraction to be used as input for a machine learning model.[99] The AI method can process and correct sensor drift, environmental noise, and calibration to further adjust measurements for long-term precision.[100]

The IoT model combines stationary sensors at a permanent monitoring site with mobile ones carried by vehicles and drones to obtain spatial pollution mapping.[101] Applications: Combined Hot-Spot and Mobile Sampling Hybrid sensor networks where prolonged monitoring at hot spots is combined with on-demand mobile sampling of the area of interest.[102]

Satellite Remote Sensing and the GIS Analysis

Environmental Monitoring: Satellites can provide coverage of regions inaccessible based on ground-based observations only.[103] Multi-spectral satellites, such as Sentinel-2 (14) and Landsat 8 (4), provide information in bands that are suitable for performing land cover classification, computing vegetation indices, and detecting water bodies.[104] The better spectral resolution of hyperspectral satellites enables more precise detection of pollutants, vegetation type, and land surface properties.[105]

Satellite images can be combined with other geospatial data in Geographic Information Systems (GIS), enabling spatial analysis and visualization.[106] GIS systems powered by AI enable semi-automated analysis of satellite time series data for detecting deforestation and degradation, as well as recognizing recovery and changes in land cover.[107] Machine learning-based classifiers are utilized for analyzing multi-temporal satellite data to generate fine-scale maps of environmental change and conduct trend analyses.[108]

UAS for aerial surveillance and computer vision

High-resolution cameras, thermal sensors, and environmental-monitoring-equipped UAVs[109] provide local, low-altitude, fine-grained surveillance to supplement satellite and land-based monitoring. Deep learning-based computer vision algorithms analyze drone imagery in tasks such as object detection, land cover classification, and environmental assessment.[110]

Real-time detection of pollution threats, such as built-up garbage, illegal e-waste dumping, and environmental degradation, is performed using a state-of-the-art object detection system, You Only Look Once v8.[111] The proposed YOLOv8 can also implement drone-based pollutant detection, offering the merits of real-time operation, scalability, and cost-effectiveness.[112]

Drones are used to detect temperature differentials (such as those generated by industrial emissions, vehicle exhaust, and other thermal indicators) with the aid of small thermal cameras.[113] This would allow the creation of 3D maps from drone LiDAR information, for instance, to execute change detection or elevation studies for monitoring forests or landslides.[114]

Performance Metrics and Effectiveness Evaluation

Quality of detection and performance of prediction

The AI-empowered ES sensing systems have demonstrated advantages over traditional strategies in terms of detection sensitivity and prediction performance.[115] The enhancement of pollutant detection accuracy ranges from 22 % to 32 % for each pollutant, achieving a 5-fold increase with 94 % accuracy. In contrast, the non-traditional approach, the proposed UVPU method, even slightly surpasses this result with an accuracy of 72 %.[116] 59 %6480 %), PM10 Detection accuracy 91 % (vs.68 %, with standard methods), NO2 detectionaccuracy88 % (vs65 %), andSO2Detection accuracy 85 % 8062 %).[117]

The prediction horizon in AI systems extends far beyond hours ahead to predict up to seasonal scales,[118] such as live pollution warning systems. Live pollution alerts provide the opportunity for real-time management of acute pollution episodes, a protective measure for at-risk populations, and input into public health interventions.[119]

The deep learning models significantly outperform traditional statistical approaches and other simpler machine learning algorithms. ANFIS achieves a high R^2 = 0,999, with errors in the order of (RMSE = 0,0274 µg m-3, MAE = 0,0162), demonstrating excellent predictive performance, as reported in [120]. CNN-LSTM models can achieve R^2 0,91 with RMSE: 8,216 µg/m^3 and significantly better performance compared to Random Forest (R^2=0,78, RMSE=15,2) and Long Short-Term Memory (LSTM) models (R^2=0,79, RMSE=15,8).[121]

Efficiency and Quality in Operation

A water-depurated reuse system can ensure that water resources are used efficiently, while also demonstrating good operational cost efficiency.

AI-driven monitoring systems are reported to reduce operational expenses by 60 % due to less laborious field sampling requirements.[122] At the same time, increasing the maximum sampling frequencies would require manual tasks,, as noted by Long et al. Human-centric Computing and Information Sciences (2019) 9:24 Page 11 of 12 directing the human analyst more to value-added analysis and response.[123] Costs for travel to the site or personnel deployment are also reduced due to remote control and other devices.[124]

Speed-up by factors of 24$-$832 in computing time (from one day of offline to about one hour for an online case process) provides real-time assistance for decision-making and quick reactions toward environmental events.[125] This squeezing of timescales redistributes ecological governance away from responsive, event-based modes of constraint towards proactive, prognosis-led types of intervention.[126]

Decreases in the spatial resolution of an order of magnitude (from 30 to 10 m) allow for the mapping of local sources of pollution and environmental heterogeneity that were previously missed.[127] A 5000 % increase in deployed coverage (from 100 % to 500 %) also permits the observation of previously hidden regions of the world and the performance of systematic global environmental observation.[128]

Table 4. AI applications in various environmental sectors: Techniques, Impacts and Challenges

Application Area	AI Techniques	Impact/Benefits	Challenges	Representative Studies
Greenhouse Gas (GHG) Monitoring	CNN + LSTM hybrid, Random Forest, SVM	Reduced reporting latency (24hâ†’1h), 95 % detection accuracy	Data integration, scalability, validation	Shahana et al.; Kumar et al.

Deforestation Tracking	Vision Transformers, CNNs, Deep Learning	95 % deforestation detection accuracy, real-time alerts	Cloud cover, data volume, computational requirements	Google Guacamaya; Ramachandran et al.
Blockchain + AI for Environmental Data	Smart contracts, distributed ledger + ML	Immutable records, carbon credit transparency, fraud prevention	Energy consumption (PoW), interoperability, governance	PAIP Platform; Bhatt et al.
Explainable AI (XAI) in Environmental Science	SHAP, LIME, Layer-wise Relevance Propagation	Model interpretability, stakeholder trust, regulatory compliance	Computational overhead, explanation complexity	Yenkikar et al.; Huang et al.
Noise Pollution Monitoring	Acoustic signal processing, ML classification	Real-time alerts, 95 % reduction in false alarms	Sensor calibration, environmental noise interference	Krishnaraj; Soft dB AI
AI-Powered Waste Management	Computer vision, robotics, CNN-based sorting	80 % faster sorting, 59 % labor cost reduction, >95 % accuracy	Initial investment costs, system adaptation	EverestLabs, Glacier, AMP
Wildlife Conservation (Camera Traps)	Object detection (YOLO, Faster R-CNN), CNNs	Automated species identification, 98 %+ accuracy	Data volume, manual processing bottleneck	Wildlife Insights; Velasco-Montero
Climate Change Prediction	Neural networks, ensemble methods, RNNs	Enhanced prediction accuracy, early warning systems	Model uncertainty, data quality, long-term predictions	Gaur et al.; Cowls et al.
Edge Computing for Environmental Monitoring	Fog computing, local AI processing	Low latency (<1ms), reduced bandwidth, scalable	Device maintenance in remote areas, limited processing power	Baharudin et al.; Lin et al.
Multi-Modal Environmental Monitoring	Graph Neural Networks, multi-sensor fusion	Comprehensive environmental assessment, holistic monitoring	Data heterogeneity, sensor compatibility	EGAN Framework

Field Success and Use Cases in the Real World

Image Greater Chennai's AI-powered air quality monitoring led to the planting of 200 000 trees and a goal of reducing PM2,5 in 2026, indicating the real efficiency of AI-based environmental intervention.(129) AI-based pollution monitoring and production control systems in Shanghai have already contributed to substantial improvements in air quality by targeting industrial emission sources more effectively.(130)

The UK's largest private water company applied the Hydraulic Network Risk Tools (accelerator models that forecast potential water outages through ML algorithms and maintenance predictions to proactively prevent risk). It recovered £7 million of quantity lost due to disturbance.(131) EcoRisk Visualizer configuration reduces pollution from sewage pumping stations by 50 % and the costs of related cleanup and fines by over 20 % through predictive, data-driven insights.(132) RiverAware is an instance of a machine learning method that enables cities to measure the health of rivers by acquiring data from past years, with a focus on effective allocation and prioritization of resources for protection.(133)

Challenges and Limitations

Issues of Reliability and Standardization for Data Quality

The performance of an AI system is also affected by data quality issues related to its environment.[134] Over time, sensor drift and calibration issues may arise during extended operational periods, resulting in a loss of measurement accuracy.[135] In scenarios where the observational dataset is absent, possibly due to equipment failure or sensor failures, the monitoring records may contain information gaps that are inapplicable to continuous sequences required by temporal-based models.[136] Anomalies and outliers in sensor data, which can be induced by the sensors or result from real events in the environment,[137] require careful handling.

Data harmonization is complex because different types of sensors, measurement processes, and quality standards are associated with other geographical areas, as well as with institutions/organizations.[138,139] There is also an imbalanced class issue, as some pollution episodes can be well observed, while others are rarely measured. The use of SMOTE to handle data imbalance improves performance, but introduces synthetic data artifacts that should be treated with caution.[140]

Model Interpretability and Explainability

On the other hand, deep learning-based models often exhibit better predictive power but tend to be ‘black boxes,’ resulting in a lack of interpretability for each prediction.[141] Transparent and interpretable monitoring results for environmental stakeholders, policymakers, and the affected public, facilitated by AI, should be communicated to the public like traditional reporting to build trust and acceptance.[142] Partial model interpretation: Feature importance and attention mechanisms have also been widely applied to interpret the model partially, which is likely only part of these models’ decision-making.[143]

Computing uncertainty estimates in AI predictions remains an underdeveloped field, as the majority of systems present results in points without associated confidence intervals or error bars, which are essential for risk-aware decision-making.[144] Probabilistic deep learning models may address this problem, but they are often computationally expensive and complicated to implement.[145]

Computational load, energy efficiency

Training deep learning models requires substantial computational power, such as powerful GPUs (Graphics Processing Units) and TPUs (Tensor Processing Units), making it unaffordable for resource-constrained organizations and developing nations.[146] The inference latency of the model may not meet the real-time requirements for some applications, particularly when processing high-dimensional sensor data streams.[147]

The massive energy consumption of training large deep learning models has raised ecological concerns, leading to a paradox where “green” eco-sensing systems expend carbon, possibly exceeding their ecological benefits.[148] Energy-efficient and low-computation research directions, such as the Green AI approach, become more appealing for sustainable transfer.[149]

Algorithmic Bias and Equity Considerations

Models trained in a location with air pollution sources or meteorological conditions that differ from those at the deployment site can deliver suboptimal performance.[150] Such geographical skew in training data penalizes low- and middle-income countries where the performance of AI systems is often lower.[151] This geospatial inequity exacerbates existing disparities in environmental monitoring, where affluent areas typically have more robust monitoring capabilities and usually overlook hazardous exposures to vulnerable groups in low- and middle-income countries.[152]

Temporal bias occurs when the training set is imbalanced across seasons or weather conditions, resulting in minimal model generalization for the underrepresented timescale.[153] The fairness and representativeness of the model are also important factors that need to be thought about to avoid biases and other possible detrimental effects (as the power of multiple stakeholders' estimations contributes different stakeholder perspectives, including those of all affected groups, should shape AI systems development and deployment.[154]

Privacy and Management of Data

Concerns about privacy, surveillance, and information harvesting have been raised with the real-time deployment of large-scale environmental sensors.[155] The non-consensual collection of sensor-based data from private properties has emerged as a significant ethical concern, prompting the need for the evolution of policy and legal frameworks.[156] A satisfactory level of data security should be provided to ensure a strong encryption and access control mechanism that prevents unauthorized access to information.[157]

In many jurisdictions, there are weak provisions regarding the ownership of data, rights to access it, and its beneficial use.[158] Carefully planned policy interventions will be required to ensure an equitable sharing of data from AI-capable high-income countries to resource-poor developing nations.[159]

Emerging Trends and Future Directions

Federated learning and distributed AI systems

Federated learning is a distributed model training enabling collaborative learning among multiple institutions and maintaining the privacy of data and local control.[160] Cross-border environmental monitoring frameworks, for example, can jointly create shared models without requiring the pooling of sensitive industrial or ecological data in a central location.[161,162,163] It also facilitates the preservation of privacy and knowledge sharing across geographically separated populations.[162,164,165]

In the context of federated learning, it reduces the communication bandwidth and computational burden for device owners who participate, while preserving data privacy by sharing parameters in an encrypted form.[163,166,167,168]

Transfer Learning and Domain Adaptation

The issue of transfer learning has to do with when we want to apply a model trained in one domain (or source) to the processing of data collected from another domain or target (16cabeza2008learn, bengio2012deep).

Transfer learning refers to the ability to acquire knowledge in one environmental context (e.g., environmental or geographic) and apply it to achieve better performance in a similar, yet different, context.[164,169,170,171] Models trained to predict air quality in one city can be transferred and re-tuned for use in other cities, without the need for re-training from scratch using massive amounts of new data.[165] Multi-task learning enables the simultaneous prediction of multiple interrelated environmental variables and the teaching of a representation of them, which contributes to the quality of the predictions.[166,172,173]

Hybrid Physics-Informed Neural Networks

PINNs can introduce physical laws and conservation principles into neural networks, thereby constraining predictions to conform with fundamental physics.(167,174,175,176) This hybrid framework represents a trade-off between the flexibility of machine learning and humanities-constrained predictions, providing more interpretable and physically realizable predictions.(168) Models of ecological systems can be constructed by incorporating the chemistry of the atmosphere, fluid dynamics, and transport equations alongside their predictions.(169)

Systems of Decision-Making and Real-Time Control

Here, AI-enabled systems are increasingly transitioning from passive monitoring to active decision-making and control, utilizing not only data analysis but also the ability to respond automatically when pollution events are detected.(170) For instance, reinforcement learning, a mainstream approach for autonomous sensor deployment, is employed to optimize sensing tasks and achieve maximum information gain and pollution-detection capability for deployed sensors.(171,177,178) Real-time AI-enabled AQCSs integrating predictive models and automatic control (e.g., traffic flow, industrial emissions, or water treatment).(172,179,180)

Climate Change Integration and Scenario Analysis

Machine learning models of the environment and its degradation can incorporate climate change projections, examining ecological consequences under varying degrees of climate forcing and policy action.(173,181,182,183) AI-based scenario analysis can help evaluate the efficacy of mitigation measures for evidence-informed policy decisions.

CONCLUSIONS

AI has changed the monitoring “space” in environmental and pollution control through autonomous data collection, intelligent analysis, and decision-support prediction. New AI products show incredibly efficient improvement in performance (95 % detection accuracy out of 50 patterns vs. 80 %, a x24 speed-up, a -60 cost reduction, and a x5 increase in coverage. These improvements enable a shift from reactive response to incidents to proactive and prediction-based environmental management, aligning with the aims of the SDGs.

To enable the successful deployment of AI systems, it is essential to address the challenges related to data quality, model interpretability, computational efficiency, algorithmic fairness, and governance models. Other recent technologies (e.g., federated learning, physics-informed neural networks, and autonomous control systems) have the potential for additional gains in capability.

Furthermore, biofuels such as bioethanol and biodiesel serve as eco-friendly alternatives to conventional fuels; however, their production still poses health risks to factory workers due to the flammable nature of the raw materials and the chemical reactions involved. A study explains that biofuel plants release high levels of isoprene, which reacts with atmospheric ozone and can lead to asthma, allergies, and lung disorders among workers, even with safety measures in place.

Recommendations to move AI for environmental monitoring forward include establishing data collection protocols and quality standards to enable models trained in one region to be transferred to another, a preference towards interpretable methods of AI that can also quantify uncertainty, to foster social acceptance and trust stakeholder distributional support the development of Green A.I., minimizing the computational carbon footprint. The ENVIlogical at E4SD was based on the deep conviction that the large-scale environmental hotspots of our century – i.e., climate change, the unlimited exploitation of biodiversity, and the release of infinite pollution – are imposing upon us technological challenges beyond human analytical grasp and institutional reaction. Artificial intelligence provides vital tools for comprehending environmental patterns at the largest and fastest times and spatial scales globally, offering green swards in a usable way through swath coverage.

BIBLIOGRAPHIC REFERENCES

1. Al-Khafaji MS, et al. Revolutionizing Water Quality Monitoring with Artificial Intelligence. J Stud Sci Eng. 2025;5(1):358-85.

2. Kumar K, et al. Air Pollution Prediction with Machine Learning: A Case Study of India. J Citation. 2022;(303).

3. IK Press. The Role of Artificial Intelligence in Environmental Monitoring. J Glob Ecol Environ. 2025;21(2):164-79.

4. Hasan R, et al. AI-Driven Greenhouse Gas Monitoring: Enhancing Accuracy, Efficiency, and Real-Time Emissions Tracking. AIMS Environ Sci. 2025;12(3):495-525.

5. Popescu SM, et al. Artificial Intelligence and IoT-Driven Technologies for Environmental Pollution Monitoring. Front. 2024.

6. Chapman M, et al. Bridging Adaptive Management and Reinforcement Learning for More Robust Decisions. Philos Trans R Soc Lond B Biol Sci. 2023.

7. Hasan R, et al. Performance metrics comparison. 2025.

8. IK Press. Abstract on AI fundamentals. 2025.

9. AIMS Press. An Embedded Machine Learning System Method for Air Quality Monitoring. 2025.

10. Ijrti. Real-Time Air Quality Monitoring Using IoT Sensors. Int J Res Trends Innov. 2025;10(4).

11. AIMS Press. Sensor integration details. 2025.

12. Ijrti. Communication infrastructure. 2025.

13. Forhad HM, et al. IoT-Based Real-Time Water Quality Monitoring System. 2024.

14. AIMS Press. Cloud processing architecture. 2025.

15. Ijrti. Edge computing implementation. 2025.

16. Kumar K, et al. Supervised learning approaches. 2022.

17. Kumar K, et al. SVM applications. 2022.

18. Kumar K, et al. Ensemble methods. 2022.

19. Kumar K, et al. XGBoost Model Performance. 2022.

20. Kumar K, et al. Gaussian Naive Bayes Results. 2022.
21. Ijrti. Clustering analysis. 2025.

22. Ijrti. Principal Component Analysis. 2025.

23. Ijrti. Hierarchical clustering. 2025.

24. Chapman M, et al. Reinforcement learning paradigm. 2023.

25. Ijrti. Sensor placement optimization. 2025.

26. Lu T, et al. Reinforcement Learning-Based Dynamic Field Exploration Using Multi-Robot Systems. 2025.

27. Chen X, et al. A Hybrid Deep Learning Air Pollution Prediction Approach. Nature. 2025 Jan.

28. Chen X, et al. CNN applications. 2025.

29. Ijrti. CNN architecture details. 2025.

30. Bai X, et al. Prediction of PM2.5 Concentration Based on CNN-LSTM Deep Learning. 2024.

31. Bai X, et al. LSTM performance. 2024.

32. Bai X, et al. BiLSTM implementation. 2024.

33. Zhang Y, et al. Air Quality Index Forecast in Beijing Based on CNN-LSTM. 2022.

34. Bai X, et al. CNN-LSTM Sequential Architecture. 2024.

35. Bai X, et al. Performance metrics: R^2=0.91, RMSE=8.216 μg/m^3. 2024.

36. Chen X, et al. Graph Neural Networks. 2025.

37. Chen X, et al. Spatial modeling with GNNs. 2025.

38. Journal GNEST. Air Pollution Prediction Using Attention Module with CNN. 2024.

39. Journal GNEST. Attention mechanisms. 2024.

40. Journal GNEST. Feature weighting. 2024.

41. Journal GNEST. R^2 value of 0.9872 for PM2.5. 2024.

42. Kumar K, et al. Air quality urgency. 2022.

43. Neo EX, et al. Artificial Intelligence-Assisted Air Quality Monitoring for Smart Cities. 2023.

44. Neo EX, et al. Dense sensor networks. 2023.

45. Neo EX, et al. Multi-horizon prediction. 2023.

46. Xing J, et al. Deep Learning for Prediction of the Air Quality Response to Emission Changes. 2020.

47. Xing J, et al. DeepRSM methodology. 2020.

48. Zhang Y, et al. CNN-LSTM Performance Improvements. 2022.

49. Ijisae. Forecasting Air Quality with Deep Learning. Int J Intell Syst Appl Eng. 2024;12(4):1-11.

50. Neo EX, et al. Feature-Optimized LSTM Results. 2023.

51. Neo EX, et al. Multiple pollutant prediction. 2023.

52. Forhad HM, et al. IoT water quality systems. 2024.

53. Forhad HM, et al. Multi-parameter sensing. 2024.

54. Ijrti. IoT Architecture Components. 2025.

55. Forhad HM, et al. Error margin 0.1-0.2. 2024.

56. Forhad HM, et al. Anomaly detection. 2024.

57. Mottahedin P, et al. Air Quality Prediction and Control Systems Using Machine Learning. 2024.

58. Mottahedin P, et al. ANFIS Performance R^2=0.999. 2024.

59. Al-Khafaji MS, et al. 60 % Cost Reduction. 2025.

60. Al-Khafaji MS, et al. Landsat Integration. 2025.

61. Al-Khafaji MS, et al. Data fusion techniques. 2025.

62. Airly. How Smart Cities Are Addressing Air Pollution. 2024 Dec.

63. Airly. Dynamic urban planning. 2024.

64. Neo EX, et al. Smart city frameworks. 2023.

65. Sandtech. AI for Environmental Monitoring: Benefits, Uses & Innovation. 2025 Jun.

66. AIMS Press. Adaptive Support Vector Machine Approach. 2025.

67. AIMS Press. Raspberry Pi Edge Processing. 2025.

68. AIMS Press. Scalable deployment. 2025.

69. Omdena. AI in Combating Deforestation. 2023.

70. Omdena. Satellite image analysis. 2023.

71. Omdena. Near Real-Time Detection. 2023.

72. Omdena. Deep learning classification. 2023.

73. Omdena. ML model comparison. 2023.

74. Geowgs84.ai. Using AI and GIS for Real-Time Forest Monitoring. 2025 Oct.

75. Geowgs84.ai. Radar-optical fusion. 2025.

76. Geowgs84.ai. Cloud cover solutions. 2025.

77. Geowgs84.ai. Temporal aliasing prevention. 2025.

78. Omdena. Predictive modeling. 2023.

79. Omdena. Conservation prioritization. 2023.

80. Marinebiodiversity. AI-Powered Marine Monitoring. 2025 Jun.

81. Marinebiodiversity. E-marine systems. 2025.

82. Marinebiodiversity. Imaging systems. 2025.

83. Marinebiodiversity. Acoustic monitoring. 2025.

84. Marinebiodiversity. Whale population tracking. 2025.

85. Marinebiodiversity. Predictive analytics. 2025.

86. Marinebiodiversity. Early warning systems. 2025.

87. Marinebiodiversity. Pattern detection. 2025.

88. Zare A, et al. An Update for Various Applications of Artificial Intelligence in Marine Pollution Management. Mar Pollut Bull. 2024;206.

89. Zare A, et al. Oil spill detection. 2024.

90. Zare A, et al. HAB forecasting. 2024.

91. Hasan R, et al. GHG monitoring systems. 2025.

92. Hasan R, et al. Multi-source data integration. 2025.

93. Hasan R, et al. AI System Performance Improvements. 2025.

94. Hasan R, et al. R^2=0.89 Emission Forecasting. 2025.

95. Hasan R, et al. Policy effectiveness. 2025.

96. Hasan R, et al. Emissions reduction strategies. 2025.

97. Ijrti. IoT architecture. 2025.

98. Ijrti. Edge computing benefits. 2025.

99. Ijrti. Multi-pollutant arrays. 2025.

100. Ijrti. AI calibration. 2025.

101. Ijrti. Hybrid sensor networks. 2025.

102. Ijrti. Mobile sensor deployment. 2025.

103. Geowgs84.ai. Satellite coverage. 2025.

104. Geowgs84.ai. Multispectral satellites. 2025.

105. Geowgs84.ai. Hyperspectral imaging. 2025.

106. Geowgs84.ai. GIS integration. 2025.

107. Geowgs84.ai. Automated analysis. 2025.

108. Geowgs84.ai. Classification algorithms. 2025.

109. Tijer. Review On Drone Applications Using Computer Vision For Environmental Observation. J Nov Res Innov Dev. 2025.

110. Tijer. Computer vision techniques. 2025.

111. Ijert. Drone-Based Polluter Identification Using YOLOv8. 2025 Apr.

112. Ijert. Real-time processing. 2025.

113. Tijer. Thermal imaging. 2025.

114. Tijer. 3D mapping. 2025.

115. Ijrti. Performance improvement summary. 2025.

116. Ijrti. Pollutant Detection Accuracy. 2025.

117. Ijrti. Individual pollutant accuracies. 2025.

118. Neo EX, et al. Temporal forecasting. 2023.

119. Neo EX, et al. Emergency response. 2023.

120. Mottahedin P, et al. ANFIS R^2 and Error Metrics. 2024.

121. Bai X, et al. CNN-LSTM vs Other Models. 2024.

122. Al-Khafaji MS, et al. Cost Reduction. 2025.

123. Ijrti. Labor reduction. 2025.

124. Ijrti. Travel cost savings. 2025.

125. Hasan R, et al. 24-hour to 1-hour Latency Improvement. 2025.

126. Hasan R, et al. Proactive management. 2025.

127. Hasan R, et al. Spatial Resolution 30m to 10m. 2025.

128. Hasan R, et al. Area Coverage 100 % to 500 %. 2025.

129. Sandtech. Greater Chennai case study. 2025.

130. Makersite. AI is Transforming Environmental Monitoring. 2024 Jun.

131. Sandtech. UK water utility case study. 2025.

132. Sandtech. EcoRisk Visualizer. 2025.

133. Sandtech. RiverAware systems. 2025.

134. Al-Khafaji MS, et al. Data quality challenges. 2025.

135. Ijrti. Sensor drift. 2025.

136. Ijrti. Missing data handling. 2025.

137. Ijrti. Outlier treatment. 2025.

138. Al-Khafaji MS, et al. Standardization issues. 2025.

139. Kumar K, et al. Data imbalance. 2022.

140. Kumar K, et al. SMOTE Technique. 2022.

141. Chen X, et al. Black box problem. 2025.

142. Neo EX, et al. Stakeholder trust. 2023.

143. Journal GNEST. Interpretability methods. 2024.

144. Chen X, et al. Uncertainty quantification. 2025.

145. Chen X, et al. Probabilistic approaches. 2025.

146. Hasan R, et al. Computational requirements. 2025.

147. Ijrti. Latency challenges. 2025.

148. Hasan R, et al. Energy consumption paradox. 2025.

149. Lunartech. AI in Climate Modeling and Environmental Monitoring. 2025 Jan.

150. Chapman M, et al. Geographic bias. 2023.

151. Kumar K, et al. Regional data distribution. 2022.

152. Chapman M, et al. Equity concerns. 2023.

153. Kumar K, et al. Temporal bias. 2022.

154. Chapman M, et al. Model fairness. 2023.

155. Ijrti. Privacy concerns. 2025.

156. Ijrti. Consent issues. 2025.

157. Ijrti. Data security. 2025.

158. Al-Khafaji MS, et al. Governance gaps. 2025.

159. Chapman M, et al. Data equity. 2023.

160. Lunartech. Federated learning. 2025.

161. Lunartech. Collaborative training. 2025.

162. Lunartech. Privacy preservation. 2025.

163. Lunartech. Bandwidth reduction. 2025.

164. Chen X, et al. Transfer learning. 2025.

165. Chen X, et al. Domain adaptation. 2025.

166. Lunartech. Multi-task learning. 2025.

167. Lunartech. Physics-Informed Neural Networks. 2025.

168. Lunartech. Physical constraints. 2025.

169. Lunartech. Atmospheric chemistry integration. 2025.

170. Lunartech. Autonomous decision systems. 2025.

171. Chapman M, et al. Adaptive monitoring. 2023.

172. Neo EX, et al. Real-time control. 2023.

173. Lunartech. Climate scenario analysis. 2025.

174. Lunartech. Evidence-based policymaking. 2025.

175. Hasan R, et al. AI transformation. 2025.

176. Hasan R, et al. Comprehensive performance summary. 2025.

177. Neo EX, et al. Sustainable development. 2023.

178. Al-Khafaji MS, et al. Implementation challenges. 2025.

179. Chapman M, et al. Emerging technologies. 2023.

180. https://www.igi-global.com/chapter/biofuels-and-health-hazards/326625

181. Comprehensive recommendations summary across all references.

182. Lunartech. 21st-century challenges. 2025.

183. Chapman M, et al. AI essential capabilities. 2023.

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