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Artificial Intelligence and Machine Learning in Environmental Health Science: A Review of Emerging Applications

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Abstract: *Artificial Intelligence (AI) and Machine Learning (ML) are transforming environmental health science because they allow the deep analysis of multi-dimensional, raw measurements or signal-level information gathered across a variety of data sources coming reliable satellite imagery, IoT sensors, epidemiological databases, and genomic data. The paper reviews the potential of AI and ML to change environmental health as it applies in predicting air and water quality, forecasting and predicting vector-borne diseases, climate change impacts on health, and models of risk of toxicity of a chemical compound. Other critical issues that have been addressed in the study are data heterogeneity, model accuracy, scalability, algorithmic bias and ethical issues associated with data privacy and transparency. The obstacles towards the implementation of AI/ML solutions in low-resource environments are addressed with particular focus, and the dangers of the situation exacerbating health disparities are determined by data deficits and insufficient infrastructure. In sum, the review makes the conclusion that, on the one hand, AI and ML provide a liberating potential in environmental health research and policy, but, on the other hand, their benefits will be optimized when applied in collaboration with human expertise, ethical regulation, and inclusion in data collection practices to make sure of its equitable, responsible implementation.*

Keywords: *AI, ML, Environmental Health, Air Quality, Water Quality, Climate Impact, Toxicity, Ethics, Data*

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1.0 Introduction

1.1 Background and Importance of Environmental Health Science

Environmental health science is an interdisciplinary science which examines the effects of environmental exposures e.g. pollutants found in air, water and soil on human health and ecosystems. It can be used as a foundation of public health, which is dedicated to predetermining environmental risk factors, assessing exposure routes, and guiding mitigation interventions to minimize the impact of disease and increase exposures to well-being (Landrigan et al., 2018). Climate change, urban air pollution, hazardous waste, contaminated water, and pesticides exposure are among the issues increasingly being associated in chronic diseases like asthma, cardiovascular diseases, neurodevelopmental disorders, as well as cancer (Pruss-Ustuen et al., 2016). Environmental health science is very important in this context in guiding regulatory measures and policies about public health. In a sense, the magnitude of data about environment and health is reproaching the conventional methods of environmental health research. To illustrate, the increase in real-time environmental sensor, satellite imaging, omics, and health records has led to high-dimensional, spatiotemporal data that cannot be meaningfully analyzed without sophisticated computation tools (Snyder et al., 2013; Topol, 2019). Such transition has paved the way to the attempt of incorporating the features of Artificial Intelligence (AI) and Machine Learning (ML) technologies into environmental health inquiries.

The upward surge in computational sophistication and the massively increased data in connection with environmental/ health information has led to the emergence of new forms of data-driven technology capable of aiding decision-making in environmental health sciences. In comparison to such traditional statistical methods, AI and ML algorithms can learn complex nonlinear dependencies between data and can perform better as additional data are obtained (Ching et al., 2018). This is because these tools are more and more used to identify environmental pollution trends, exposure disease risk modeling, climate health impact forecasting, and to address environmental monitoring initiatives. As an illustration, satellite images have been analyzed using deep learning models with the help of which air quality and dispersion patterns could be predicted (Ardila et al., 2019). Unsupervised ML methods were also involved in detecting clusters of disease outbreaks linked to environmental factors (Ezzati & Kammen, 2002). These new possibilities evidence how AI/ML can change how environmental health research and practice can be done.

1.2 Objectives of the Review

This review aims to discuss the new uses of AI and ML in environmental health science. It seeks to bring in an awareness of the use of these technologies to track environmental pollutants, determine the health risk, establish trends of a disease due to environmental exposure, and make better decisions in the public health policies. Furthermore, the review also discusses the possibilities, restrictions, and the future of the sphere of AI/ML incorporation, thus giving a clear impression of the potential of their breakthrough power..

2. 0 Foundations of AI and ML in Environmental Health

2.1 What is AI and ML Paradigms?

Artificial Intelligence (AI) and Machine Learning (ML) are fast changing the environmental health science landscape to a more profound analysis of heterogeneous large data sets and improved decision-making capacities. The essence of these technologies is in core learning paradigms, namely, supervised, unsupervised and reinforcement learning, having their own specific ways of extracting knowledge in the form of data.

Supervised Learning

One of the most common ML paradigms supervised learning employs labeled input-output pairs to train a model (Nnenna et al., 2025). It uses prior examples of explicit input-output mappings (e.g. of environmental variables to instances of disease incidence) to learn to map new inputs to outputs. Such a method is especially applicable to environmental health, including forecasting the level of air pollution, exposure risk, and predicting health outcomes associated with environmental stressors (Kim & Lim, 2024). Used algorithms of supervised learning are linear regression, support vector machine (SVM), random forests, and deep neural networks (Olawale et al., 2020). As an example, a supervised model can be used to forecast asthma emergency room visits based on information on the air quality and meteorological data as they appeared in the past (Chen et al., 2023).

Unsupervised Learning

On the contrary, unsupervised learning is the one that looks at unlabeled data and is concerned with discovering hidden patterns or inherent structures on datasets (Areghan, 2023). It has particular advantages in grass-roots health situations when the links among variables are not realized or little comprehended (Chinnamgari, 2021). Clustering techniques, dimensionality reduction, and association rule mining are the methods employed with the purpose to gather like environmental events or to display suspicious trends (Jia & Pei, 2025). As an example, one can train one of the clustering algorithms, e.g., k-means or DBSCAN, to find geographic areas having a similar pollution history or signal an extraordinary increase in the level of a contaminant necessitating some type of public health action.

Reinforcement Learning (RL)

Another method that is less frequently used but very promising in the environmental health science is reinforcement learning. It entails an agent and an environment where the agent receives feedback measured in rewards or punishments and makes decision based on the action. RL is mainly applicable to dynamic decision-making systems, including adaptive traffic control to minimize urban air pollution, real-time environmental monitoring or smart energy use systems (Jia & Pei, 2025). Though its use is yet to become widespread, RL does present a significant opportunity to systems that must optimize their performance over time in the constantly fluctuating environment and policy settings (Chinnamgari, 2019).

Collectively, the learning paradigms are the flexible framework to tackle a wide range of issues in environmental health, including forecasting the levels of exposure to environmental stressors, establishing the patterns of the environmental risks, as well as, maximizing response to crises in the area of population health.

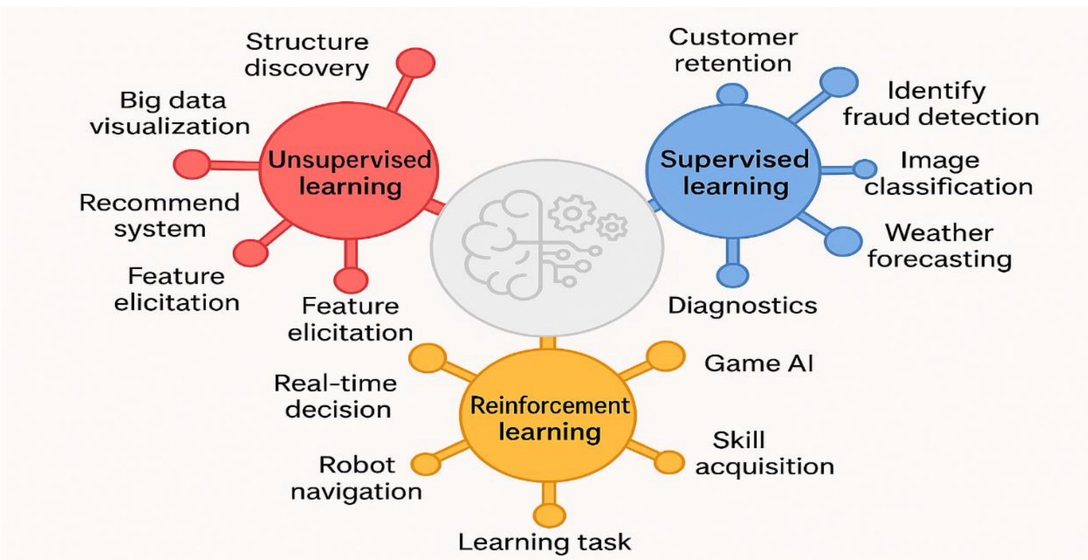

Fig 1: Image showing the different applications of Machine learning (After Pugliese et al., 2021).

2.2 Data Types and Sources in Environmental Health Science

Environmental health science AI and ML use data as a starting point as core input. Combining large and heterogeneous data is the key to the development of the models that can appraise risks, predict outcomes and contribute to evidence-based policymaking. These data sources are becoming more in the multimodal nature, integrating spatial, temporal, biological, and behavioral streams of data.

2.2.1 Data Given by Satellite and Remote Sensing

The satellite data give a macroscopic or in many instances global view of the environmental situation over years. Such datasets will be surface temperature, vegetation indices, urban heat signature, and concentrations of atmospheric gases. As an illustration, the data of NASA: MODIS (Moderate Resolution Imaging Spectroradiometre) and Landsat programs, and European Space Agency Sentinel satellites have been heavily applied during controlling the changes in land-use, wildfires, urban heat islands, and the levels of fine particulate matter (PM2.5)(Seltenrich, 2014). Such datasets can be used in modeling environmental exposures and evaluating related health risks, like cardiovascular disease, heatstroke, or respiratory illness when analyzed with the help of AI algorithms (Utomi et al., 2024).

2.2.2 Environmental sensor and IoT Data

Due to smart city technologies and Internet of Things (IoT) devices, there is now a possibility to collect environmental data in real-time and at high spatial resolution. These are air quality sensors (e.g. PM2.5, Ozone, CO_2), noise monitors, water quality probes, and temperature / humidity probes. Such data are used by AI models to identify environmental threats, trace pollution spreading, and predict health warnings in city conditions (Zhu et al., 2023). Personal exposure monitoring devices carried by the individuals and usually designed as part of a smartphone payload offer a human-scale aspect of environmental health monitoring, and give individual exposure data down to the personal level (Adeusi et al., 2024).

2.2.3 Epidemiological and Health Records

Providing specific epidemiological data like hospital admissions, morbidity/mortality registries, birth records, and health surveys enables the process of linking the two phenomena of environmental exposures and health outcome. These are usually availed by the health departments or the national health system. These records have been examined using machine learning in order to find patterns and associations: how high pollution days might be related to more children with asthma brought to the hospital, or how climate-related migration might affect human health in the long term (Chen et al., 2023). Such records, combined with environmental data, can be used to guide early warning systems, and better distribute medical resources.

2.2.4 Climatic and Weather Information

Institutional weather and climate data such as NOAA or ECMWF give important contextual data regarding temperature, precipitation, wind patterns, and humidity. These are the main confounders and effect modifiers during environmental studies of health. To take an example, air pollution may be determined by temperature and humidity, which impacts respiratory health (Ezzati & Kammen, 2002). These complex interactions can be captured through AI and ML models to assist in predicting the result of health threats under various climatic conditions (Ademilua & Areghan, 2022; Okolo et al., 2025).

2.2. 5. Geographic Information Systems (GIS) and Spatial Data

The GIS projects combine the spatial data layers like population density, traffic, land use, industrial emission, and topography in order to make the exposure modelling of the environment in various areas possible. Hot-spots mapping, exposure zoning, and health disparity analyses at the multiple scales (e.g., city blocks, zip codes, national levels) can be performed using machine learning analysis of GIS datasets (Zareba et al., 2023). ML spatiotemporal models can detect emergence environmental health risks in near real-time (Nnenna et al., 2025).

2.2. 6. Biomonitoring and Genomic Data

To a certain extent, exposure and health risk are reflected in biomonitoring data (blood or urine toxin or metabolite samples), to a greater extent in genomic data indicating susceptibility to environmental agents and are perceived as being personal to the individual. The use of ML algorithms, particularly the deep learning and ensemble approaches, to combine omics statistics with environmental exposures data, discover vulnerable populations or forecast long-term disease prognoses, is rising (Ching et al., 2018).

Table 1: Common Data Sources for AI/ML in Environmental Health Science (Adapted from Ezzati & Kammen, 2002; Zhu et al., 2023; Zareba et al., 2023)

Data Source	Type of Data	Typical Use Cases in AI/ML	Strengths	Limitations
Satellite Imagery (MODIS, Sentinel)	Spatial, optical, radiometric	Air quality modeling, land-use classification, climate exposure	Broad coverage, historical archives	Lower resolution, cloud cover interference
IoT Sensors	Real-time sensor data	Exposure alerts, pollution forecasting, localized health warnings	High temporal resolution, cost-effective	Sensor drift, maintenance, data gaps
Health Records	Clinical, epidemiological data	Disease mapping, health outcome prediction	Direct link to health outcomes	Privacy concerns, data incompleteness
Meteorological Data	Weather parameters	Climate-adjusted exposure models, seasonal risk forecasting	Publicly available, global access	Spatial mismatch with local exposures
GIS and Demographic Data	Population, land use, proximity	Risk zoning, vulnerability analysis, spatial disparity assessments	Fine-scale mapping, rich contextual data	Integration challenges with other datasets
Biomonitoring/Genomic Data	Molecular, omics data	Susceptibility prediction, personalized exposure risk	Personalized insights, predictive modeling	Complex, requires domain expertise

3. 0 Emerging Applications of AI and ML in Environmental Health

The effects of Artificial Intelligence (AI) and Machine Learning (ML) introduction into the environmental health science field are the spread of paradigm-left observational methods as data-driven, predictive, and real-time analytical models. As environmental data and data on the public health become more complex and significant, AI/ML algorithms are helping to identify environmental hazards, disease outbreaks, and health risks at a higher rate of precision (Adesola et al., 2025). Some of the five important areas where such technologies have had significant influence were explored in this section.

3.1 Quality AQ monitoring and pollution forecasting

A leading problem of air pollution in the environment entails cardiovascular diseases, respiratory disorders, and premature deaths across the globe (WHO, 2021). The conventional air surveillance uses a limited ground-deployed sensor network that cannot frequently record spatial gradients in contamination concentrations, particularly in environments with poor resources. The current solution to the air pollution problem lies in the ML models that collate the heterogeneous data on satellite images, weather, road traffic, and land-use patterns to forecast the concentration of air pollutants, e.g., PM 2.5, NO_2, and O_3, with a high spatiotemporal resolution (Wang et al., 2020; Chen et al., 2023). Accurate prediction systems have been formed using such algorithms as the random forests, support-vector regressions and deep learning algorithms (e.g. convolutional neural networks). As an example, Di et al. (2019) applied gradient boosting machines on continental United States, obtaining high accuracy when estimating daily PM 2.5 exposure by combining satellite aerosol optical depth, meteorology, and the land-use data.

3.2 Anomaly detection and Water Quality Evaluation

Cases of water borne diseases and chemical pollution of waters are a menace in the world, especially in the developing world. Water quality observation can be cumbersome because it requires laboratory test and random sampling which is costly. AI/ML-based solutions allow predicting water quality and detecting anomalies in real-time and identifying the source of contamination. Artificial neural networks (ANNs), decision tree, unsupervised clustering algorithms have been used to predict important indicators, such as pH, turbidity, biological oxygen demand (BOD), heavy metals and microbial contamination (Eliades et al., 2023). As an example, ANN models have been effectively implemented in modelling river water quality in terms of parameters such as temperature, flow rate and conductivity (Ahmed et al., 2019). Unsupervised learning can be applied especially when it is necessary to identify irregularities in the water system, e.g., anomalous increase in the level of contamination that can point to breaches in the pipes or illicit dumping.

3.3 Environmentally Driven Disease Prediction

Vector-borne diseases such as malaria, dengue, Zika virus and Lyme are increasingly being predicted using AI/ML since they are sensitive to the environmental factors temperature, precipitation, humidity, and land cover. Learned supervised ML models are able to recognize the trends in past disease incidence and match it with environmental factors to construct predictive models. As an example, both random forest and gradient boosting were displayed to be quite accurate when predicting dengue epidemics based on weather and demographic data (Ansari et al., 2024). Satellite imagery and GIS layer applications have been considered as geospatial ML which is employed in mapping the hotspots of breeding mosquitoes and other diseases vectors. To go even further, even image-based detection of larvae living conditions and the identification of species vectors were performed with deep learning models (Kittichai et al., 2021).

3.4 Modeling of Health Effects of Climate Change

Climate change influences the health of the population by means of extreme affects of the weather, food insecurity, pollution air pollution, and proliferation of communicative disorders. AI/ML techniques play a significant role in the modeling of nonlinear, lagged, or indirect climate-health interactions that cannot be addressed in a short term. To provide an example, ML models can be trained to forecast mortality caused by heat, predict shifts in disease vectors in climatological scenarios, or compute the impact of flooding on water-borne diseases (Watts et al., 2018). The concept of reinforcement learning has gone as far as being offered to real-time adaptation measures in climate-sensitive healthcare infrastructure. Also, AI has been applied to climate-related displacement and climate-related disaster conditions in which future mental health burdens can be modeled, until now using little quantitative methodology (Crane et al., 2022).

3.5 Analysis of risk of chemical and toxic exposure

AI/ML has transformed the way risk assessment of chemicals and toxicology is done. Conventional toxicology tends to depend on animal experiments which are slow and ethically limited. ML also offers alternative ways of predicting the chemical toxicity based on chemical structure descriptors, route of exposure, and biological activity profile (Zorn et al., 2020). The ML algorithms make predictions of the toxic nature of new compounds using QSAR models. Also, graph neural networks (GNN) and other deep learning models are capable of learning the complex, multi-dimensional form of molecular structures and discover pathways to a molecule toxicity. Data in the form of toxicogenomics-measured gene expression levels are also analyzable, utilizing the ML to gain insight into the connection between environmental chemical exposures and the results of such contact with biological response and health outcomes (Zorn, et al., 2020).

Fig 2: Various applications of AI in environmental science (After Wang et al., 2020)

4.0 Challenges and Ethical Considerations

Though Artificial Intelligence (AI) and Machine Learning (ML) may hold immense transformative potential in the field of environmental health, when deployed, they pass along a plethora of technical, ethical, and contextual issues. This should be addressed critically to adopt them fairly, responsibility and sustainably, particularly in cases of public health where human lives and equity are on the line.

4.1 Technical Hurdles: Accuracy of models, data heterogeneity and Scalability

The accuracy and applicability of models to environmental health science are one of the most important technical challenges of applying AI/ML in realizing its potential. Model trained on a single geographical area or a type of data was found to fail miserably when transferred to another region because of the variance in environmental, social, or infrastructural aspects (Chen et al., 2023). In addition, AI models are susceptible to the quality of input data, with all its noise, missing, and biased data capable of drastically lowering the predictive reliability. The other problem is that of data heterogeneity. The datasets are usually of environmental health and are presented in a variety of platforms and formats, including satellite remote sensors and IoT sleeves; hospital reports and mobile apps shared across differing resolutions, sample rates, and metadata standards (Ching et al., 2018; Ajibola et al., 2024; Emmanuel et al., 2024).

Table 2: Summary of Emerging Applications of AI and ML in Environmental Health Science (Adapted from Kittichai et al., 2021; Watts et al., 2018)

Application Area	AI/ML Techniques	Input Data	Primary Outputs/Goals
Air Quality Monitoring and Pollution Prediction	Random Forest, SVR, DNN, LSTM	Meteorology, satellite AOD, land use, traffic, sensor data	$PM_{2.5}$ and NO_2 forecasting, pollution mapping, short-term alerts
Water Quality Assessment and Anomaly Detection	ANN, Decision Trees, K-Means, Autoencoders	pH, BOD, turbidity, DO, sensor data	Real-time water quality prediction, anomaly detection, contamination alerts
Vector-Borne Disease Prediction	Random Forest, XGBoost, CNN, SVM	Temperature, rainfall, NDVI, GIS layers, disease records	Outbreak prediction, vector hotspot mapping, habitat classification
Climate Change Health Impact Modeling	LSTM, Regression, Decision Trees, NLP	Climate projections, temperature, flood data, disaster records, social media	Heatstroke prediction, flood risk, disease shifts, mental health surveillance
Toxic and Chemical Exposure Risk Analysis	QSAR (RF, SVM), DNN, GNN, Ensemble Models	Molecular descriptors, SMILES strings, toxicogenomic data	Chemical classification, toxicity prediction, exposure biomarkers

Standardizing and preprocessing of such disparate streams of data to feed into a model is associated with complexity and hence can bring in error and be resource-intensive (David & Edoise, 2025). The other technical constraint is scalability. Such effective deep learning models, e.g., need huge computational resources and curated data that are not likely to be within reach in most academic and governmental environments (Ansari et al., 2024). Some ML models (e.g., deep neural networks or ensemble models) are also costly in terms of the computing resources required to retrain or employ them in real-time decision-making application, which is not suitable in situations where an environmental health disaster is occurring, time is of essence.

4.2 Ethical Concerns: Data Privacy, Algorithmic Bias, and Transparency

The debate around the use of AI/ML in environmental health is growing based on its ethical issues. One of the most critical is the data privacy in a situation whereby personal health records, geolocation information or biometric sensors data are used. When merged with environmental exposures data, such datasets are likely to produce the field of re-identification and in small or marginalized groups (Topol, 2019). Moreover, AI algorithmic discrimination is a thoroughly examined topic. When the training data mimics preexisting social or environmental imbalance e.g. lack of representation of low socio-economic or rural communities, the trained models can reinforce or even increase the imbalance (Pruss-Ustun et al., 2016). This may arise in the form of false classification of pollution threat areas in the environmental health or distribution of health resources unequally. A close issue is absence of transparency, which in many ML models is often identified as the so-called black box nature of such models. It can be that training complex models including deep neural networks can achieve good predictive performance but fail to help understand causality or explanation of their results (David & Edoise, 2025). That weakens trust and interpretability that are essential to policymaking and effective communication in health science (Rudin, 2019).

4.3 Challenges in Deploying AI/ML in Low-Resource Settings

AI and ML have the biggest potential to improve environmental health in low- and middle-income countries (LMICs), where the burden of the environment and disease is greatest. Nevertheless, they are the grounds where AI/ML tools struggle the most to become implemented. The two main issues are a lack of digital infrastructure, a lack of quality data, and lack of technical expertise. As an example, a model learned in a high-income urban area may not apply in rural environments unless adapted, because of the difference in sources of air quality, climate, and access to the health system (Hadley et al., 2020). Also, the data obtained in such environments could be based on a paper health records system, underreporting, or on the absence of long-term environmental monitoring. This brings an important sense of equity in AI innovation into the question, are we developing systems based on the requirements of most affected individuals? Devoid of comprehensive information and purposeful transfer processes, AI/ML advances have potentials of furthering the global disparities in environmental health outcomes (Alami et al., 2020).

5.0 Conclusion

The ability of the environmental health science to integrate Artificial Intelligence (AI) and Machine Learning (ML) solutions is a big step in the future compared to the past that used conventional methods of analyzing. Such technologies have demonstrated a great potential in areas like air and water quality assessment, predicting occurrence of disease that is vector-borne and/or that is sensitive to conditions brought about by climate change, or assessing risks of chemical toxicity whereby researchers and policymakers have been able to address challenges in environmental health in a much better manner. Nevertheless to achieve this potential, several critical technical and ethical issues need to be solved. Such problems as data heterogeneity, the challenge of models being insufficiently generalizable across regions, computational requirements, and privacy and data transparency should be addressed carefully. Moreover, the use of AI/ML tools in the conditions of low resources is also limited due to the lack of data infrastructure and technical knowledge, corresponding to the issues of equity and inclusiveness.

On the whole, though AI and ML will dramatically improve environmental health science, their ability to do so will be hinged on their combination with human-based governance, diverse data mobilization, and robust ethical regulation. The focus on these elements will also contribute to the empowerment of such technologies in serving equitable, responsible, and effective public health benefits to various communities.

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