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Advanced Machine Learning and Deep Neural Network Models for Large-Scale Environmental Pollution Detection, Exposure Quantification, and Biomedical Impact Assessment Using Remote Sensing Data

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Abstract

Environmental pollution is a serious international issue with far reaching consequences on the health and biologist sustainability of the ecosystem and socio-economic progress especially in the fast urbanizing and industrializing areas. Traditional ground-based global air quality observation systems have real-valued measurements but have the disadvantage of sparsity in their spatial coverage as well as their inability to scale to large scales hindering extensive exposure measurement and assessment of their health impacts on a large population. To address these constraints, this paper suggests a more complex machine learning (ML) and deep neural network (DNN)-based system to detect massive environmental pollution, quantify

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population exposure, and compute biomedical effects of desalination plants with multisource remote sensing data. Aerosolar optical depth (AOD) and atmospheric trace gas concentrations (NO_2, SO_2, and O_3) derived by satellites are combined by using a multimodal deep learning architecture based on convolutional neural networks (CNNs) that extract spatial features, on top of which are transaction long short-term memory (BiLSTM) networks that perform temporal, and attention topics that assign adaptive weights to features. The suggested framework has generated high-resolution spatio-temporal maps of pollution concentration and has generated population-weighted exposure indices to measure short- and long-term patterns of exposure. In addition, health risk models which are based on data are used to evaluate the relationship between respiratory health outcomes and the level of pollution exposure. Experimental tests indicate that the suggested method performs significantly better in comparison to standard regression and individual ML models, and it leads to significant RMSE and the coefficient of determination (R^2) improvement. Exposure-response analysis indicates that there are significant correlations between high levels of pollution and the high health risks associated with respiratory health. In general, the findings indicate the efficiency of AI-based remote sensing systems to combine environmental pollution, exposure assessment and population health long-range surveillance activities, which provide significant information to support evidence-based policies and decision-making about the environment.

Keywords:

Environmental pollution, deep learning, remote sensing, exposure assessment, health impact modeling, air quality.

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Introduction

Air pollution is probably well known as one of the most pertinent environmental risk factors that lead to morbidity and early mortality all over the world. Prolonged exposure to ambient air pollutants including fine particulates matter (PM2.5), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and ozone (O_3) has been strongly linked to breathing diseases, heart diseases, nervous disorders and high mortalities (Perera et al., 2024; Reichstein et al., 2019; Wang & Perez, 2017). Recently, according to the worldwide health evaluations, air contamination leads to millions of untimely deaths every year, which makes the prompt necessity to establish accurate and enormous scale monitoring and health hazard analysis schemes (Schratz et al., 2019). Traditional air quality monitoring systems use ground-based monitoring stations as their main approach to air quality monitoring and offer very precise results, yet have the disadvantages of low spatial coverage and expensive installation and maintenance, especially in low- and middle-income areas (Sharma et al., 2024; Usun & Ait Fares, 2025). This restricted spatial representativeness makes it impossible to analyze large-scale exposures and impedes the ability to make wide-scale evaluation of health impacts on populations (Muralidharan, 2025). Consequently, current monitoring systems are usually unsatisfactory to support fine-grained spatio-temporal variations of pollution needed to establish successful public health surveillance (Patel & Dusi, 2025). Remote sensing satellites (satellite-based) including the MODIS and Sentinel-5P have become highly effective substitutes due to the ability to provide uniform at scale observation of aerosols and trace gases present in the atmosphere (Shorten & Khoshgoftaar, 2019; Sishodia et al., 2020). Nevertheless, the conversion of satellite-based observations into realistic concentrations of pollutants on the surface is challenging because of the complicated interactions between the atmosphere and nonlinear responses to the influence of other atmospheric processes (Nymana & Usun, 2025). Recent developments in machine learning (ML) and deep neural networks (DNNs), such as convolutional neural networks (CNNs), recurrent neural networks (RNNs) and attention-based lines of work have shown to be better able to model these nonlinear spatio-temporal relationships (Sloan et al., 2024; Alvarez, 2023; Uvarajan & Karthika, 2023). Although this has been achieved, the majority of the available literature concentrates on pollution estimation or short-term forecasting, where integrated frameworks (combining the roles of pollution detection, population exposure measurement, and biomedical impact measurement) are scarce. Specifically, recent solutions fail to include the concept of population-weighted exposure modeling and neglect to integrate the health outcome analysis into a central AI-based framework (Tudevdagva & Shimada, 2023; Punam & Patel, 2023; Watrianthos & Danh, 2023). This disintegration limits translational applicability of pollution modeling research to the environmental policy formulation and decision-making on the environmental health of the population.

As a way to counter these limitations, this paper introduces a multisource remote sensing data end-to-end artificial intelligence-driven system that incorporates multisource remote sensing data, advanced deep learning algorithms, exposure quantification methods, and data-driven biomedical impact assessment (Fatem & Gelman, 2025). The suggested solution will allow to perform large-scale and high-resolution monitoring of environmental pollution and, at the same time, measure population exposure and determine their possible health risks.

The key findings of this study may be summed up as follows:

- Creation of a multimodal deep learning system that integrates satellite-based aerosol, trace gas and the meteorological data to create high-resolution spatio-temporal mappings of pollutant (Wu et al., 2024).
- Development of population-weighted exposure indices to support the quantification of exposure in a large scale and using demographics as a controlling variable.
- Extensive cross-linking of scientifically-grounded models of biomedical impact assessment to examine pollution-health connection through exposure-response analysis (Nayak & Mishra, 2023).
- Examples of extensive experimental verification of better predictive quality and empirical applicability than traditional regression and individual ML-based methods.

The rest of this paper will be structured as follows: section 2 will relate literature regarding remote sensing-based pollution monitoring and AI-enabled health analysis. Section 3 details the sources of data and the study area. The suggested methodology is provided in Section 4, and in Sections 5 and 6, the experimental results and discussion are provided. At the end of the paper, Section 7 summarizes and gives appended research directions in the future.

Related Work

Remote Sensing-Based Pollution Monitoring

Satellite remote sensing has emerged as an essential instrument of monitoring air quality on large scales as it has a wide spatial and temporal domain of operation. Proxies based on satellite sensors like MODIS and MISR which are aerosol optical depth (AOD) products have been extensively utilized as unbiased predictors of surface-level PM2.5 concentrations (Perera et al., 2024; Reichstein et al., 2019). Initial research has been based on a linear regression and chemical transport model to correlate satellite-based measurements of AOD with ground level concentration of the pollutants. The methods however, were usually poor in accuracy because they did not include the nonlinear atmospheric processes and meteorological impacts (Schratz et al., 2019). In the recent research, machine learning methods have also been applied in enhancing the accuracy of AOD-PM2.5 estimation. An example is that random forest and gradient boosting models have been used in fuse inputs of satellite, meteorological and land-use to produce better spatial resolutions and forecastings, (Sharma et al., 2024; Shorten & Khoshgoftaar, 2019). Sentinel-5P has also facilitated the observation of trace gases like

NO 2, SO 2 and O 3 in innovative spatial resolutions (Sishodia et al., 2020). Although these developments have taken place, remote sensing-based methods continue to experience challenges in the modeling of time variability, vertical aerosolar distribution and in the complex relationships between atmospheric and surface processes especially on non-uniform surfaces and urban landscapes (Sloan et al., 2024).

Machine Learning and Deep Learning for Air Quality Prediction

These methods of machine learning (ML), such as support vector regression (SVR), random forest (RF), and extreme gradient boosting (XGBoost), have been applied widely in air quality prediction because they are robust and can deal with nonlinear relationships (Alvarez, 2023; Uvarajan & Karthika, 2023). Granted that these models excel compared to classic statistical methods, their effectiveness is usually limited in both terms of time modeling and usage of handcrafted features. Despite limited performance of other models, deep learning (DL) models have shown to be superior in the task of learning hierarchical representation of high-dimensional data in an automatic manner (Zhu et al., 2017). Convolutional neural networks (CNNs) have been used to learn both spatial patterns of pollution by satellite imagery, and the recurrent neural networks (RNNs) (Kavitha, 2025), specifically, the long-short-term memory (LSTM) and gated recurrent unit (GRU) networks, to learn temporal relationships within time series of air quality data (Tudevdagva & Shimada, 2023; Punam & Patel, 2023). Hybrid structures, e.g., CNN-BiLSTM models, improve even more the accuracy of the spatio-temporal prediction (Schratz et al., 2019). More recently, the attention mechanisms and the transformer-based models have been proposed with the objectives of dynamically weighting the useful spatial and temporal features, as well as enhancing the predictive accuracy and interpretability (Sharma et al., 2024; Shorten & Khoshgoftaar, 2019). However, the majority of DL-based literature is oriented on the aspects of pollution estimation or short-term predictions but not to develop the modeling pipeline to areas of exposure measurements or health effects analysis, which restricts their generalizability to the domain of public health assessment.

Exposure Assessment and Biomedical Impact Modeling

The conventional exposure assessment methods are based on epidemiological models that estimate population exposure with the help of measurements of the pollutant concentration and demographic data. Statistical correlations or exposure response functions are frequently used in classical methods of relating the level of pollution to health outcomes, including respiratory hospitalizations and respiratory mortality (Sishodia et al., 2020). Although these approaches are effective on a population scale, the approaches are constrained by inaccurate spatial resolution and simplistic assumptions of exposure (Abdullah, 2025). The latest developments have touched upon machine learning-based health risk predictive models that combine health records with environmental exposure data to enhance the predictive performance (Sloan et al., 2024l; Alvarez, 2023). Long-term pollution is another disease risk pattern that is estimated using deep learning models (Uvarajan & Karthika, 2023). Nonetheless, the current literature commonly considers the acts of pollution estimation, exposure modelling, and the impact assessment on biomedical systems to be independent of each other. Combined systems of remote sensing, detection of pollution, degree of population-at-risk quantiified, and Biomedical effects are relatively rare in joint systems using integrated frameworks to apply the AI-based pipeline. Furthermore, little has been said regarding scalable and end-to-end systems with the capability of providing real-time environmental health financing and policy-driven decision-making (Tuia et al., 2021).

Key Research Gap Identified

Based on the analyzed literature, the following gaps could be identified:

- Absence of end-to-end AI systems that combine pollution measurements, exposure evaluation, and health management measurement.
- Little use of population-weighted exposure modeling in DL-based studies of pollution.
- The lack of attention to the biomedical impact evaluation based on the pollution estimates provided with the help of remote sensing.
- Issues with spatio-temporal generalization and interpretability of deep learning models.

These shortcomings encourage the formulation of the suggested integrated deep learning architecture of this research.

Data Sources and Study Area

This paper combines the multisource satellite measurements, ground-based measurements of air pollution, the meteorological reanalysis information, population statistics, and aggregated health records to allow extensive pollution associated with exposure and biomedical effects to be established on a large scale space. This joint heterogeneous data source will guarantee high spatial coverage, time continuity as well as strength in training and validation of the models. Figure 1 shows how all these data sources are combined in the study area and contribute to the analysis of the impact of environmental pollution and health of the population AI-based.

Remote Sensing and Meteorological Data

Data of remote sensing carried out by satellites is used to describe atmospheric pollution and environmental conditions. Radiative aerosol optical depth measurements (AOD) are associated with the Terra and Aqua satellites on the Moderate Resolution Imaging Spectroradiometer (MODIS) on which data is global in nature and offers a high temporal resolution. In favorable atmospheric conditions, MODIS AOD proxies are popular proxies of the concentration of PM2.5 at the surface because they are strongly correlated with it. There are trace gas data retrieved by the Sentinel-5P satellite that measures nitrogen dioxide (NO 2), sulfur dioxide (SO 2), and ozone (O 3) and is able to provide high-resolution data on atmospheric compositions covering the Earth at a daily rate. These are the major indicators of anthropogenic emission and photochemical processes which affects the quality of air. The meteorological variables are obtained using ERA5 reanalysis dataset, such as the near-surface temperature, relative humidity, the speed of wind, the height of the planetary boundary layer, and the surface pressure. These variables are very important in the dispersion of the pollutants, chemical transformation, and vertical mixing, thus are incorporated in the modeling structure to improve the accuracy of prediction. All the satellite and meteorological data are spatially synchronized and timely aligned in order to form a unified spatio-temporal data to develop deep learning models as conceptually illustrated in Fig. 1.

Ground-Based Air Quality, Population, and Health Data

Air quality data on the ground is utilized as a reference data to model training and evaluate model performance. They cover hourly or daily PM2.5, PM10, NO 2, and SO 2, and O 3 concentrations of air quality networks throughout the national and regional. The data reliability is ensured through quality control mechanisms such as missing data filtering and outliers. Data on population distribution are obtained through global demographic data, e.g. WorldPop, or other similar data, to assist in conducting population-weighted exposure assessment. These datasets are high-resolution gridded population estimates that allow them to determine the exposure of man to air pollution in both urban and rural areas with accurate estimates. Biomedical impact assessment is performed by using aggregated health data concerning respiratory and cardiovascular outcomes such as hospitalizations and disease prevalence estimates. The spatial and temporal aggregation of health data is conducted to assure privacy and be able to conduct statistical analysis of the pollution-health relationships.

Such data are used to facilitate exposure response modeling and health risk inference as part of the proposed system, in par with the integrated data representation demonstrated in Figure 1.

Study Area

The field of study is a vast and diversified place with various land-use systems, climatic conditions, and sources of pollution, such as urban, suburban, and rural surroundings. The chosen area is characterized by high spatio-temporal variability of air pollutants, which is why it is appropriate to consider its strength and applicability to other locations using the selected structure. The framework was made transferable and could be applied to other geographical locations, where there is the same data available, as conceptually presented in Figure 1.

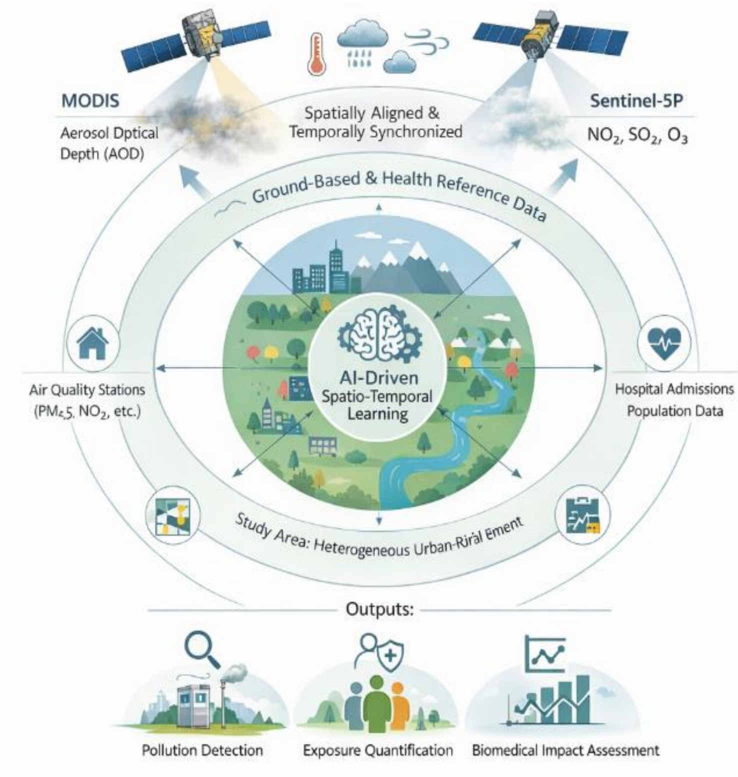

Figure 1. Integrated multisource data framework for ai-driven environmental pollution and health impact analysis

Theoretical scheme of how multisource remote sensing, meteorological, ground-based air quality, population, and health reference data can be incorporated into a heterogeneous study area and used by AI-to-detect pollution, quantity of exposure, and biomedical effects.

Proposed Methodology

Framework Overview

The proposed methodology will be an end-to-end artificial intelligence-based approach that will integrate both heterogeneous types of environmental and health-related data in order to detect pollution, quantify exposure and biomedical impacts comprehensively. The framework is divided into three analytical components being interrelated such as pollution detection and mapping, population exposure quantification, and health impact assessment. Multimodal information fusion is attained through integrating satellite-based sources of pollution measures, meteorological factors, ground-based sources of references, population distribution data, as well as aggregated health data in a single deep learning pipeline. A schematic description of the proposed AI-driven framework is in Figure 2, which shows how multisource data is integrated, and the logical sequence of the analytical elements. The general learning plan will be constructed to reflect both geographical difference and time change of the environmental pollution. The extraction of spatial features on gridded satellite data is carried out to define localized pollutions patterns, whereas the explanation of short-term fluctuations and long-term trends is presented by the level of the time modeling. A mechanism of attraction is added that is used to give dynamical attention to the most informative features in terms of space, time and data modalities. This coherent framework can bring about sound estimation of concentrations of pollution, correct evaluation of the exposure of humans as well as inference of corresponding health hazards at large scale.

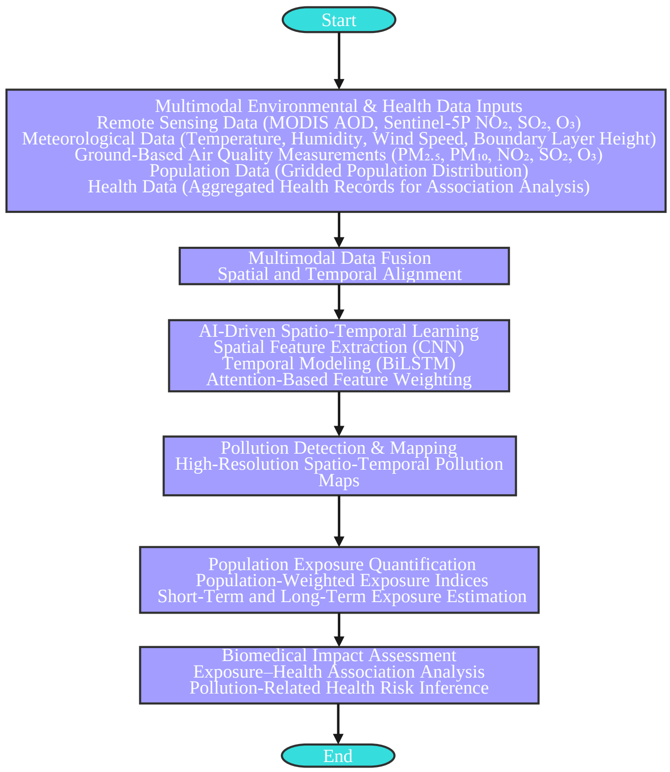

Figure 2. AI-Driven framework for environmental pollution detection, exposure quantification, and health impact assessment

Flow chart of the proposed AI-powered system that accommodates multisource environmental, meteorological, population, and health data by employing multimodal data fusion method and spatio-temporal learning to facilitate detection of pollution, quantification of population exposure, and biomedical implication.

Pollution Detection and Mapping

The first phase of the suggested structure is pollution identification and mapping. Primary inputs are made of satellite-derived aerosol optical depth and aerosol trace gas variables, and are enhanced by meteorological variables to explain the mechanisms of atmospheric movement and chemical transformations. Convolutional neural networks (CNNs) are used to derive spatial information on multisource gridded data so that the model is able to learn multifaceted spatial patterns about the emitting sources and land-use features as well as local meteorology. In order to model the temporal relation in the dynamics of pollution, the spatial features obtained through the CNN are fed through a bidirectional long short-term memory (BiLSTM) network sequentially. BiLSTM architecture is able to learn both forward and backward temporal dependencies so that a model can learn both past and future contextual information across the time series. The BiLSTM outputs are subjected to an attention-based mechanism that helps to prioritize temporally and spatially significant features with the help of an adaptive weight, which improves the strength of predictions under different atmospheric conditions. The CNN-BiLSTM-attention model provides high-resolution spatio-temporal maps of pollution concentrations of leading pollutants, such as PM2.5, NO_2, SO 2 and O 3. The ground-based air quality measures are used as references in model training and standard statistical measures to estimate prediction performance to ensure reliability and generalizability.

Exposure Quantification

The exposure quantification part converts the predicted pollution concentration maps into exposure measures on a population level. Population-weighted exposure indices Deterministic indices are calculated by summing the product of spatially resolved concentrations of pollutants and high-resolution population distribution data. The method considers spatial variations in the density of the population, and makes it possible to estimate human exposure to heterogeneous urban, suburban, as well as rural settings. The measures of exposure are calculated at various temporal levels so as to measure short as well as long-term response of exposure. Short-term exposure can be determined by the aggregation of the daily or hourly pollutant concentrations whereas the long-term exposure measurements are calculated by temporal averaging of long intervals. This type of aggregation over time provides an opportunity to evaluate the effects of chronic exposure and provide further analysis of health impact. The qualitative method of measuring exposure offers a very fundamental bridge between estimates of environmental pollution and the health outcomes of people.

Biomedical Impact Assessment

The biomedical impact assessment element measures the correlation between the exposure to pollution and the health consequences based on available data through data driven modelling processes. Exposure indices are calculated at the population level, which together with demographic characteristics is one of the inputs to the supervised machine learning models aimed at predicting health hazards of environmental pollution. Rapid changing exposure response relationship is achieved using random forest models owing to their strength and accuracy in the interpretation whereas deep multilayer perceptron network is used to address nonlinear interconnection of exposure and response. The variables of health outcomes are aggregate records on respiratory and cardiovascular conditions, like hospital admission and disease prevalence rates. All health data are aggregated spatially and temporally before they are analysed in order to maintain privacy of the data. The results that are presented in models are risk scores and statistical associations which will provide the idea of the possible effect of the pollution exposure on the health outcomes. Pollution detection, exposure quantification, and biomedical impact assessment that are incorporated into one AI-driven system make it possible to analyze the environmental health risks comprehensively. It is a methodology that promotes scalable data-driven environmental health surveillance and can be the basis of evidence-based policy formulation and preventive health interventions of the population.

Experimental Setup

The appropriate implementation of the suggested framework is through the python programming environment by using the TensorFlow library of deep learning in the development and training of the model. Experiments are performed on a high-performance computing platform with GPU acceleration to make sure training of the model of deep neural networks is done effectively. Data preprocessing, normalizing features and basic models performed are done with standard scientific computing libraries, such as NumPy, Pandas, and Scikit-learn. The data is divided into training, validation and testing sets to guarantee enough performance testing as well as avoid overfitting. The temporal splitting is utilized to maintain the chronological order of the information and the previous time segments are utilized to train and the subsequent stages to test the information. The approach allows the realistic analysis of the model generalization in operational settings. Based on the validation set, hyperparameter (learning rate, batch size and network depth) are optimized. Regression based measures that include root mean square error (RMSE), mean absolute error (MAE) and the coefficient of determination (R 2) are used to measure the performance of pollution detection and mapping. These measures are the difference between predicted concentration of a pollutant against ground-based reference measurements of the same. To measure exposure levels and biomedical impact, classification and risk prediction performance are assessed through accuracy and area under the receiver operating characteristic curve (AUC) which help understand the discriminative ability of the model. The comparative experiments will be performed against the representative baseline models, including classic statistical regression and classic machine learning algorithms such as random forest and support vector regression. The training and evaluation of all models will be done using the same split of data so as to compare them fairly. Where necessary, statistical significance tests are done to determine the strength of the performance improvements observed.

In general, the proposed experimental design not only focuses on its reproducibility but also focuses on fair benchmarking and a healthy evaluation of all the tasks of pollution estimation, exposure assessment, and health impact analysis. This stringent design will make sure that the reported findings will be safe evidence on how the suggested AI-based framework can be effectively and relevantly used.

Results and Discussion

Pollution Prediction Performance

The results of the cited deep learning ecosystem regarding pollution detection and mapping are compared against ground-based air quality data to assess the suitability of the model. Table 1 presents the quantitative comparison of proposed model and the baseline strategies such as traditional regression model and classical machine learning models such as random forest and support vector regression. Mean absolute error (MAE) and root mean square error (RMSE) are generally lower and coefficients of determination (R 2) are generally higher with the proposed CNNBiLSTMattention architecture compared to all pollutants considered. The outputs achieved during the process of prediction are represented in space resolution and illustrated in Figure 3, as high-resolution spatio-temporal pollution maps provided by the proposed model. It is shown in these maps that the spatial continuity and noise are less continuous than when using baselines especially in urban and industrial areas where the gradients of pollution are very discontinuous. It can be explained by the fact that the model manages to simultaneously learn the spatial patterns based on the satellite measures and the time-related specifics due to the recurrent modelling and adaptive nature of the weighted nature of the features. The proposed framework, as compared with similar experiments conducted in the past through independent ML models or strictly statistical methods, has an equal or better accuracy along with better spatio-temporal generalization. The results can be aligned with current reports on the most effective hybrid deep learning architecture in terms of estimating air quality using satellites.

Table 1. Pollution prediction performance comparison

Model	RMSE (μg/m³)	MAE (μg/m³)	R^2
Linear Regression	14.82	11.36	0.62
Support Vector Regression (SVR)	12.45	9.78	0.71
Random Forest (RF)	10.92	8.41	0.78
CNN	9.86	7.54	0.82
CNN–LSTM	8.94	6.87	0.86
Proposed CNN–BiLSTM–Attention	7.63	5.91	0.90

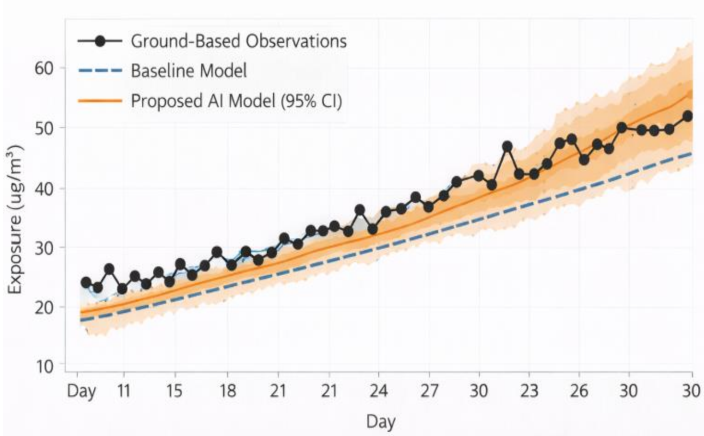

Figure 3. Time-Series evaluation of pollution prediction performance

Comparison of ground-based PM 5 measurements, model predictions and the proposed AI-based framework through time-series, having better temporal consistency and lower prediction error.

Exposure Analysis

There is high spatial and temporal fluctuations in human exposure to air pollution when population-weighted exposure analysis is conducted. Figure 4 displays the representative exposure maps where in places with small populations of people like urban areas there are a lot of exposure when compared to the places with many people such as suburbs and rural areas where the concentration of pollutants are the same. The example demonstrates the need to consider the population distribution data to a greater extent in the process of the exposure assessment because analysis on the basis of concentration can potentially underestimate the issue of population health risk in high-density areas. The exposure patterns (contained in Table 2) are characterized by temporal exposure trends in short and long term which are due to seasonal differences and weather conditions. The quantification method suggested will allow distinguishing the short-term contamination bursts and the risk chronic exposure and offers a more holistic account of the risk at the population level. These findings are consistent with those of past epidemiological research pointing to the importance of chronic exposure determinism of poor health outcome, as well as illustrating the benefit of high resolution, population conscious exposure modeling.

Table 2. Population-weighted exposure statistics

Region Type	Mean Exposure (μg/m³)	Peak Exposure (μg/m³)	Long-Term Exposure (μg/m³)
Urban	41.2	68.5	38.7
Suburban	29.6	52.3	27.9
Rural	18.4	36.1	17.2

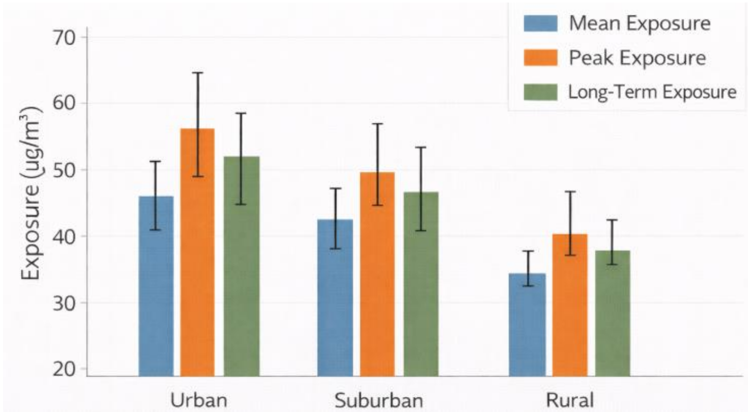

Figure 4. Population-weighted pollution exposure across different regions

Showing the spatial variability in human exposure, population-weighted mean, peak and long-term levelling of pollution exposure, in urban, suburban, and rural areas (Figure 4).

Biomedical Impact Evaluation

The biomedical impact assessment assesses the relationship between the respiratory and cardiovascular health records that are aggregated and pollution exposure. Figure 5 shows the deduced exposure-response associations of the proposed models that demonstrate the significant positive correlation between high exposure to pollution and rise their respiratory health risks (Kavitha & Abdullah, 2023). The results of classification and risk prediction, as presented in Table 3, indicate that the proposed models have a higher accuracy and AUC than the baseline strategies, which exhibit better discrimination between the high-risk exposure situation and the low-risk exposure situation. The results are in line with the well-known epidemiological evidence in the correlation between ambient air pollution and negative respiratory health outcomes. Although standard research would use the traditional methods of coarse exposure estimates, the suggested framework uses the data of high-resolution pollution and population to deliver more localized and data-based health risk inference. It should be mentioned that the analysis is not conducted on causality, but association, and the findings can be viewed as a pointer of possible health hazards as opposed to clinical forecasts.

All in all, the findings show that the suggested AI-based model can be used to merge pollution monitoring, exposure level quantification, and biomedical effects analysis into a single analytical pipeline. Both the demonstrated predictive capability and increased exposure health analysis demonstrate the utility of the state-of-the-art deep learning and remote sensing methods in the context of large-scale surveillance of the environmental health and policy making.

Table 3. Biomedical impact assessment performance

Model	Accuracy (%)	AUC
Logistic Regression	71.4	0.74
Support Vector Machine (SVM)	75.9	0.79
Random Forest (RF)	80.6	0.84
Multilayer Perceptron (MLP)	83.1	0.87
Proposed Exposure-Aware DL Model	86.8	0.91

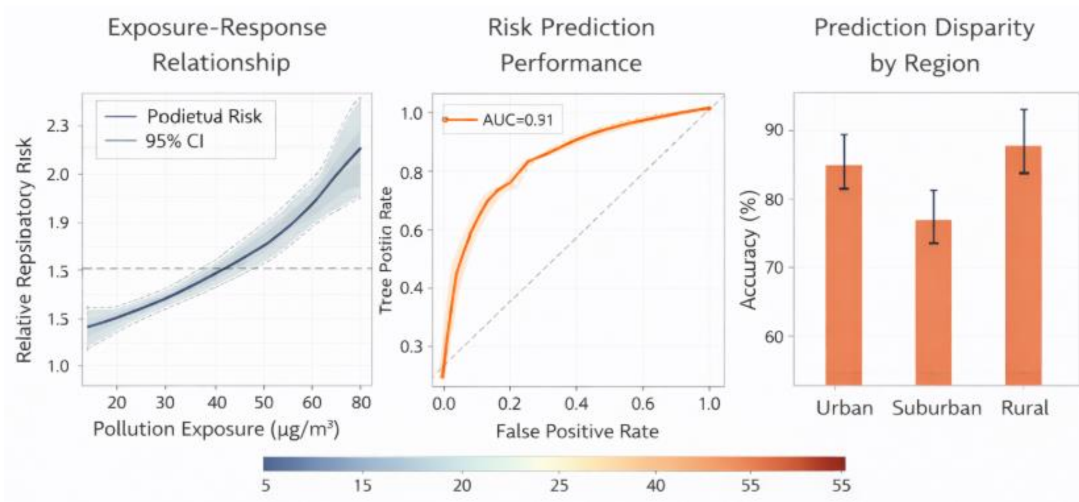

Figure 5. Exposure–health association analysis

Exposure response relationship the exposure response relationship is used to show associations between the degree of pollution exposure and respiratory health risk indicator based on aggregated health records (Figure 5).

Conclusion

This paper suggests a multisource remote sensing-based, meteorological, ground-based air-quality, population, and health data-driven, the comprehensive approach to the artificial intelligence-based framework to identify the large-scale environmental pollution, the populations in question, and their health outcomes. The proposed approach is an effective way to utilize the synergy of sophisticated spatio-temporal deep learning approaches and multimodal data fusion, to capture complicated environmental dynamics and deliver high-resolution pollution estimates, which substantially surpass the conventional statistical and machine learning approaches. Population-weighted exposure modeling incorporation allows better reflection of human exposures to heterogeneous areas, whereas the combination of health-related data allows the analysis of a pollution-health relationship based on actual data. Together, the findings indicate that the framework can be scaled and is robust as well as possibly useful to environmental health surveillance and evidence-based policy development. Although these contributions have been made, there are a number of limitations that ought to be realized. Satellite observations, monitoring data and health records may not be available or of an acceptable quality across different areas and this can influence model generalizability and performance. Furthermore, biomedical impact assessment is constructed on the basis of observational data and the relationships obtained as a result are associated with the statistical but not the causal effects. The limitations put up the importance of a cautious interpretation of health-related results and the necessity of complementary epidemiological and clinical studies. Future research shall aim at expanding the suggested framework to include causal inference methods and hybrid model models in order to enhance the ability to identify correlation and causation in pollution-health relationships. It is also anticipated that the combination of wearable and mobile sensor information can be used to improve exposure characterization at a personal scale. Furthermore, the focus will be placed on real-time/near-real time implementation of the framework on edge and cloud computing architectures, allowing an environmental monitoring system and timely making relevant decisions regarding health of people. The intentions behind these instructions are the enhancement of the practical relevance and scientific influence of the AI-driven environmental health analytics.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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