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Atmospheric Radionuclides: Physical Behavior, Exposure Assessment, Spectroscopic Surveillance, and Emerging AI-Driven Monitoring Approaches

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ABSTRACT

Atmospheric radionuclides are transported through the environment as gases or particle-associated contaminants, making their behavior closely dependent on aerosol properties and atmospheric conditions. Understanding their movement, deposition, persistence, and potential exposure pathways therefore requires integration of aerosol physics with reliable environmental surveillance. This review discusses the major physical principles governing atmospheric radionuclide dynamics, with emphasis on particle size, transport, deposition, resuspension, and interactions with radiation and light. Current exposure-assessment approaches based on environmental sampling and laboratory measurements are examined alongside emerging spectroscopic and remote sensing (SRS) technologies for atmospheric and terrestrial monitoring. Particular attention is given to the growing role of artificial intelligence and machine learning in interpreting complex environmental datasets and supporting short-term forecasting. Recent PM_{10} research demonstrates that XGBoost, CatBoost, artificial neural networks, LSTM, Bi-LSTM, and ensemble models can integrate air-quality and meteorological data to provide location-specific predictions. Although these approaches were developed for particulate air pollution rather than radionuclides, their data-driven framework provides a useful direction for future

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radionuclide surveillance. Integrating conventional measurements with SRS, sensor networks, and AI-assisted prediction could improve spatial coverage, early detection, exposure assessment, and environmental decision-making.

Keywords: Atmospheric radionuclides; Aerosols; Exposure assessment; Spectroscopic remote sensing; Machine learning; Environmental surveillance

Highlights

- Examine the physical properties governing radionuclide aerosols, including particle size, atmospheric transport, deposition, resuspension, and environmental fate.
- Reviews conventional exposure-assessment and environmental surveillance methods for atmospheric and terrestrial radionuclides.
- Discusses emerging spectroscopic and remote sensing (SRS) approaches for wider and more rapid environmental monitoring.
- Explores the integration of AI and machine learning with atmospheric monitoring and environmental datasets.
- Analyses the governing physical properties of radionuclide aerosols, including size distribution, deposition behavior, and optical interactions.
- Assesses existing exposure evaluation techniques alongside emerging spectroscopic and remote sensing (SRS) applications in atmospheric and terrestrial systems.

1.Introduction

Air pollution remains an important environmental and public-health concern worldwide. Emissions from industrial activities, transportation, fuel combustion, and other anthropogenic sources contribute to deterioration of atmospheric quality and associated health risks (Manisalidis et al., 2020; Ahmed et al., 2023, Pusuluru S et al., 2026a,b,c). The magnitude of these impacts varies considerably among regions because pollutant concentrations are influenced by emission sources, population density, land use, and atmospheric conditions. Particulate matter, particularly PM10 and PM2.5, is widely used to characterize atmospheric pollution. These particles are important from an exposure perspective because they can enter the respiratory system, with finer particles capable of penetrating deeper into the lungs (Chalvatzaki et al., 2023; Olesiejuk and Chałubiński, 2023). Major sources include fuel combustion, industrial activities, construction, and vehicle emissions. The behavior of atmospheric particles is also influenced by local meteorology, including temperature, rainfall, humidity, wind conditions, and atmospheric pressure, making their concentration highly variable across space and time (Russo et al., 2014; Lagmiri and Dahech, 2023).

These characteristics are particularly relevant to the study of atmospheric radionuclides, because radionuclides can become associated with airborne particles (Punna SK et al., 2026a,b). The movement and eventual fate of such contaminants can therefore depend on aerosol size, atmospheric transport, deposition, resuspension, and local environmental conditions (Singh R et al., 2025). Understanding particulate-matter dynamics can consequently provide useful supporting information when interpreting atmospheric radionuclide measurements, although conventional PM measurements cannot substitute for

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radionuclide-specific monitoring. The complex relationship between atmospheric particles and environmental conditions has encouraged increasing use of artificial intelligence (AI) and machine learning (ML) for air-quality assessment and forecasting. Unlike conventional approaches that may have difficulty describing nonlinear environmental relationships, ML models can process multiple variables simultaneously and identify temporal patterns within large monitoring datasets. Several algorithms have been investigated for particulate-matter prediction, including Extreme Gradient Boosting (XGBoost), CatBoost, LightGBM, Random Forest, artificial neural networks (ANN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and other deep-learning approaches (Mampitiya et al., 2023, 2024, Natishah AJ et al., 2025). Such models can integrate pollutant measurements with meteorological parameters to estimate future atmospheric conditions.

A recent investigation in the Republic of Ireland illustrates this approach. Mampitiya et al. 2024, evaluated XGBoost, CatBoost, ANN, LSTM, Bi-LSTM, and an ensemble model for forecasting PM10 concentrations across eight monitoring locations. The analysis incorporated PM10, PM2.5, NO2 and meteorological information, together with previous-day PM10 concentrations. Interestingly, PM2.5 and NO2 showed stronger relationships with PM10 than the climatic parameters considered in the study. Model performance was also location dependent. No individual algorithm provided the best predictions across all monitoring sites, emphasizing the importance of site-specific model selection and calibration. The models were subsequently used to generate 24-h PM10 forecasts, demonstrating the potential of AI-based systems for short-term atmospheric surveillance.

For atmospheric radionuclide research, this represents a promising transferable framework rather than direct evidence of radionuclide prediction. Future systems could integrate radionuclide measurements, aerosol characteristics, meteorological parameters, spectroscopic and remote sensing (SRS) observations, and historical monitoring data within AI-based models. Such integration could improve identification of spatial and temporal patterns, support early-warning systems, and potentially enable predictive assessment of contaminant transport and deposition. This combined approach may ultimately strengthen conventional sampling by moving environmental surveillance toward real-time and predictive monitoring. Overall, advances in aerosol science, environmental sensing, spectroscopic and remote sensing (SRS), and artificial intelligence are creating new opportunities for understanding atmospheric contaminant behavior. Recent applications of machine learning to PM10 forecasting demonstrate the potential of XGBoost, CatBoost, ANN, LSTM, Bi-LSTM, and ensemble models for capturing complex spatial and temporal variations in atmospheric particles. Building on these developments, this review examines the physical principles governing atmospheric radionuclide transport and fate, current exposure assessment and surveillance methods, and emerging SRS and AI-based monitoring approaches (Punna SK et al., 2026b). Particular attention is given to integrating conventional measurements with advanced sensing and predictive tools to improve early detection, exposure assessment, environmental surveillance, and decision-making for atmospheric radionuclide contamination.

2. Overview of Machine Learning Development and Applications in Atmospheric Pollution

Machine learning (ML) has evolved considerably and now provides a broad range of tools for environmental prediction. Depending on the intended application, ML approaches can support regression, classification, reinforcement

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learning, and generative modeling (Punna SK et al., 2026b). For atmospheric pollution studies, regression and time-series models are particularly important because they can estimate pollutant concentrations and forecast changes over time. The commonly applied approaches can broadly be grouped into traditional optimization-based models, tree-based algorithms, linear regression models, and modern deep-learning architectures.

Traditional ML approaches include Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs). SVMs use kernel functions to transform input variables and capture nonlinear relationships, with linear, polynomial, and radial basis function kernels commonly employed. ANNs similarly learn nonlinear relationships but use interconnected computational layers and activation functions. Early neural-network structures, including the Multilayer Perceptron (MLP), typically contain input, hidden, and output layers, with network parameters optimized during training through backpropagation. Other ANN architectures such as RBFN, GRNN, NARX, ELM, and Deep Belief Networks subsequently expanded the range of approaches available for environmental prediction. Despite the emergence of more sophisticated deep-learning methods, conventional ANNs remain useful for atmospheric pollution studies because of their relatively straightforward implementation and strong predictive capabilities.

Tree-based models have also undergone substantial development. Early decision-tree algorithms, including ID3, C4.5, and CART, provided the foundation for more advanced ensemble methods. Two major ensemble strategies subsequently emerged: bagging and boosting. Random Forest (RF) is a representative bagging approach that combines predictions from multiple decision trees, whereas boosting methods progressively improve predictions by focusing on errors generated during earlier stages. This development led to algorithms such as AdaBoost, Gradient Boosting Decision Trees (GBDT), XGBoost, LightGBM, and CatBoost, which are now widely used for both regression and classification tasks in environmental studies. Linear regression and statistical learning approaches represent another important group. Multiple Linear Regression (MLR), ARIMA, ridge regression, LASSO, Elastic Net, and Generalized Additive Models (GAMs) have all been applied to regression and time-series problems. Regularized methods such as ridge regression, LASSO, and Elastic Net help control model complexity and improve generalization. However, the comparatively limited ability of conventional linear approaches to capture highly nonlinear relationships can restrict their performance when atmospheric pollution is controlled by multiple interacting environmental variables.

The development of modern deep-learning architecture has further expanded atmospheric prediction capabilities. Convolutional Neural Networks (CNNs) are particularly effective at extracting spatial features, whereas Recurrent Neural Networks (RNNs) are designed to recognize temporal dependencies in sequential datasets. Advanced CNN architectures such as AlexNet, VGG, ResNet, and GoogLeNet introduced deeper and more efficient network designs. For time-series applications, limitations associated with conventional RNNs, particularly vanishing gradients, contributed to the development of Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs). These architectures retain relevant historical information and are therefore particularly useful for forecasting pollutant concentrations that vary over time. Further improvements in deep learning have been achieved through activation functions such as ReLU and LeakyReLU, dropout strategies to reduce overfitting, and optimization approaches such as Adam and weight-decay regularization. Collectively, these advances have improved

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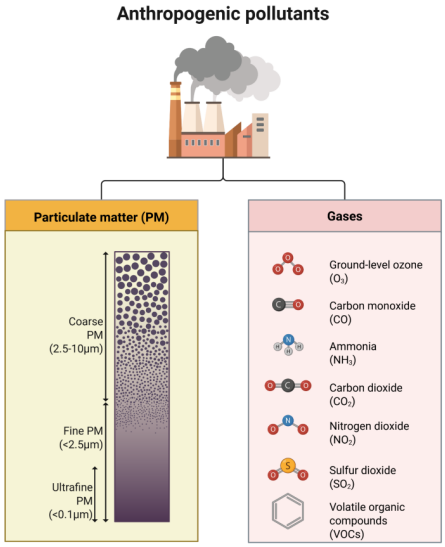


Figure 1. Schematic representation of major anthropogenic air pollutants categorized into particulate matter (PM) and gaseous pollutants. Particulate matter is illustrated based on aerodynamic diameter, including coarse particles ($PM_{2.5–10}$, 2.5–10 µm), fine particles ($PM_{2.5}$, <2.5 µm), and ultrafine particles (<0.1 µm), highlighting their size-dependent distribution. The gaseous pollutants section includes key atmospheric contaminants such as ground-level ozone (O_3), carbon monoxide (CO), ammonia (NH_3), carbon dioxide (CO_2), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and volatile organic compounds (VOCs), which are primarily emitted from industrial and combustion-related activities..

model training, convergence, and predictive stability.

2.1. Application to Atmospheric Aerosol and Pollution Prediction

The progression from conventional regression methods to ensemble learning and deep neural networks has substantially expanded the role of ML in atmospheric pollution assessment. Current applications increasingly use SVM, RF, XGBoost, LightGBM, CatBoost, ANN, CNN, LSTM, GRU, and ensemble approaches to relate pollutant concentrations to meteorological, temporal, spatial, and remotely sensed variables. These methods are particularly valuable because atmospheric pollution is governed by complex interactions that are often nonlinear and location dependent. Recent PM10 forecasting provides a practical illustration. XGBoost, CatBoost, ANN, LSTM, Bi-LSTM, and ensemble models have been evaluated for predicting particulate concentrations, with model performance varying among monitoring locations. This reinforces an important consideration for atmospheric surveillance: there is unlikely to be a single universally superior ML model, and model selection, training-data quality, hyperparameter optimization, and local validation remain essential. For the broader context of aerosol measurement, atmospheric radionuclides, and spectroscopic and remote sensing (SRS), ML offers an important pathway for combining information obtained from ground-based monitoring, aerosol measurements, meteorological observations, satellite or remote-sensing platforms, and historical datasets. Such integrated models could support pollutant mapping, source characterization, short-term forecasting, exposure assessment, and early-warning systems (Abbaszadeh M et al., 2026; Singh R et al., 2026). However, application to atmospheric radionuclides requires radionuclide-specific training and validation data; performance demonstrated for PM10 or other conventional pollutants should not be assumed to transfer directly to radioactive aerosols.

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3. Physical Principles Governing the Dynamics and Fate of Atmospheric Radionuclides

The behavior and fate of atmospheric radionuclides are controlled by a complex interplay of physical processes initiated up to their release into the atmosphere, were from natural source or anthropogenic activities such as nuclear incidents, industrial discharges, or medical waste emissions (Figure 1). A fundamental process governing these particles is radioactive decay, particularly via alpha and beta emissions, which not only determine their radiological properties but also induce positive charging through electron emission-a process referred to as self-charging. In addition to self-charging aerosol particles acquire charge through diffusion charging via ambient atmospheric ions, field charging under strong electric fields (notably during dust storms), and triboelectric charging mechanism significantly influence aerosol dynamics by affecting particle motion, aggregation (coagulation), and interactions with surrounding particles and surfaces (Hahmann et al., 2022; Brower, 2012; Blackadar, 1957; Bodini et al., 2019; Tobin et al., 2016). Coagulation processes modify particle size distribution (PSD), thereby influencing atmospheric residence times and transport distance. Larger particles tend to settle rapid under gravitational forces, whereas smaller particles remain airborne for extended periods, increasing the likelihood of long-range transport and inhalation exposure. Deposition processes-both dry (governed by gravity and electrostatic interactions) and wet (mediated by precipitation)-determine the spatial distribution and accumulation of radio nuclides on terrestrial surfaces.

Environmental variables such as wind velocity, atmospheric turbulence, temperature, and humidity further regulate aerosol transport and dispersion. In hot and arid environments, these processes are intensified: elevated temperatures and low humidity prolong particle suspension, while frequent dust storms resuspend deposited radio nuclides and enhance electrostatic charging and atmospheric electric fields. These conditions complicate aerosol dynamics and elevate potential exposure risks. Therefore. Accurate modelling of the coupled processes – including radioactive decay, particle charging, coagulation, deposition, and environmental interactions is essential for predicting radionuclide dispersion, evaluating associated health and environmental risks, and formulating effective radiological protection and emergency response strategies (Albdour et al., 2024).

3.1. Particle-Size Distribution (PSD) of Aerosol Particles

Particle-Size distribution (PSD) is a critical parameter governing the behaviour, transport and environmental fate of aerosol particles. It represents the range and relative abundance of particle size within an aerosol population, typically the range and relative abundance of particle size within an aerosol population, typically extending from a few nanometres to several hundred micrometres, resulting in substantial variations in particle mass and volume. PSDs may be characterised as continuous or discrete; however, real atmospheric aerosols commonly exhibit multimodal and polydisperse distribution due to the diverse natural and anthropogenic processes responsible for their formation and evolution (Figure 1). In desert environments, PSDs often consist of mixtures of fine and coarse particles particularly during dust events (Moemken et al., 2018; Pryor et al., 2020; Barstad et al., 2012). Inhalable particles are generally defined as those with diameter below 20 μm, while particle size smaller than 5 μm-classified as fine particles-are capable of penetrating deep over tine through processes such as coagulation, fragmentation, condensation, evaporation, deposition and resuspension. For radioactive aerosols released into the atmosphere, PSDs tend to progressively

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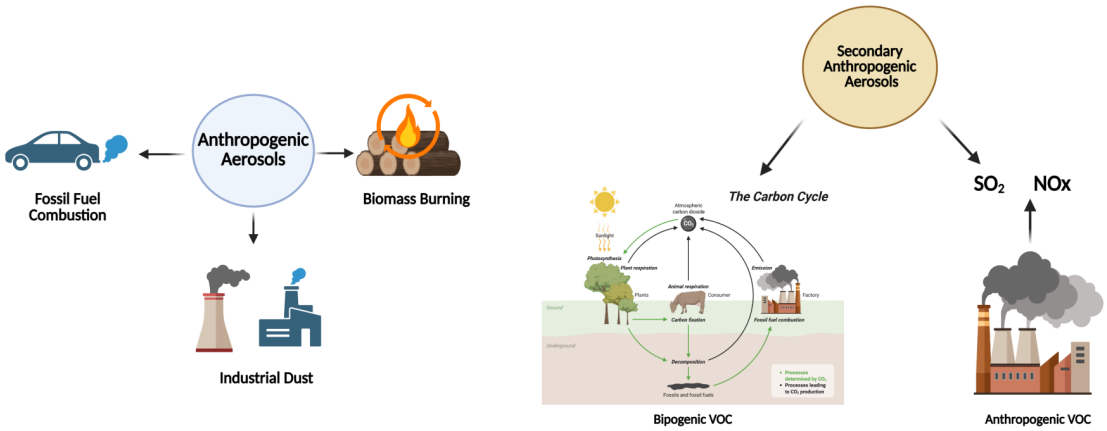


Figure 2. Sources and formation pathways of anthropogenic and secondary aerosols. Schematic representation of primary anthropogenic aerosol sources and the formation of secondary anthropogenic aerosols. Primary aerosols originate from fossil fuel combustion (e.g., vehicular emissions), biomass burning, and industrial activities, generating particulate matter such as industrial dust. Secondary anthropogenic aerosols are formed in the atmosphere through chemical transformations involving precursor gases such as sulfur dioxide (SO_2), nitrogen oxides (NOx), and volatile organic compounds (VOCs). Both biogenic VOCs, associated with natural processes such as the carbon cycle, and anthropogenic VOCs from industrial emissions contribute to secondary aerosol formation, highlighting the complex interactions between natural and human-driven atmospheric processes..

converge toward background aerosol distributions, typically dominated by particles in the 0.1-1 μm size range. This shift occurs because larger particles are rapidly removed through gravitational settling, whereas ultrafine particles are often reduced via coagulation processes. A comprehensive understanding of PSD is essential for accurately modelling aerosol transport, evaluating environmental and health impacts, and improving predictive models for radionuclide dispersion and deposition (Albdour et al., 2024).

3.2. Dry Deposition

Dry deposition represents a principal mechanism for the removal of atmospheric aerosols including radioactive particles and involves the transfer of particles from the atmosphere to surfaces in the absence of precipitation. As described in the referenced work, this process is governed by gravitational settling, aerodynamic forces, and electrostatic interactions, all of which are influenced by particle size, electric charge, and environmental conditions (Hueging et al., 2013; Reyers et al., 2016; Tobin et al., 2015). Larger particles are predominantly affected by gravitational forces and settle more rapidly, whereas smaller particles are more strongly influenced by diffusion processes and turbulent airflow. For radioactive aerosols, deposition behaviour is additionally affected by particle charge, which can either enhance or inhibit surface attachment depending on the electrical properties of the receiving surface and surrounding. Electrostatic forces, particularly those generated during dust storms or arising from the self-charging nature of radioactive particles, can significantly modify deposition patterns by attracting or repelling particles. Surface characteristics-including roughness, moisture levels, and vegetation cover-also play a critical role in determining deposition efficiency. In arid and semi-arid regions where dust events are frequent, deposition dynamics are further complicated by particle resuspension, which reintroduces deposited material into the atmosphere and challenges accurate prediction of fallout distributions. Understanding dry deposition processes is therefore essential for assessing environmental contamination and associated health risk following the release of

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radioactive aerosol, particularly under extreme climatic conditions (Albdour et al., 2024).

3.3. Mechanism of Interaction of Aerosol Optical Properties and Pollution Weather

The interaction between aerosol optical properties and pollution-related meteorological conditions is complex and plays a critical role in regulating atmospheric conditions is complex and plays a critical role in regulating atmospheric stability and radiative balance (Figure 2). Depending on their size and chemical composition, aerosols can either scatter or absorb incoming solar radiation. Ground-based lidar observations have significantly advanced the understanding of aerosol vertical distribution and its influence on boundary layer dynamics and pollutant accumulation. For instance, absorption of solar radiation by aerosols can lead to atmospheric heating, which suppresses vertical convection and reduces boundary layer height. This process facilitates the accumulation of pollutants near the surface and contribute to the development of haze and smog conditions. During pollution episodes, aerosol optic parameters-including single-scattering albedo (SSA) and aerosol optical depth (AOD)-undergo dynamic changes sue o particle growth, ageing, and chemical transformation. Elevated relative humidity further enhances aerosol scattering through hygroscopic growth, leading to reduced visibility. The study highlights that aerosol transport significantly modifies regional AOD levels and intensified pollution events in central and southern China, with contributions from both local sources and long-range transport from regions such as Asia and Burma. Consequently, a feedback mechanism involving aerosol, radiation, and meteorological conditions amplifies air pollution, particularly under stagnant atmospheric conditions associated with haze and hog (Che et al., 2024).

4. Overview of Current Exposure Assessment and Surveillance Methods

Current methodologies for assessing harmful algal bloom (HAB)-related exposure monitoring associated health impacts integrate both advanced sensing technologies and direct environmental sampling approaches. Traditional monitoring techniques involve the collection of water samples using vessels, buoys, or fixed platforms, followed by laboratory analysis to identify algal species and quantify toxin concentrations. Although these methods provide high analytical accuracy, they are resource-intensive and limited in spatial and temporal coverage.

Adaptations of conventional air pollution sampling techniques-such as filter samplers, cascade impactors, and impingers-have been employed to evaluate aerosolised HAB toxins. However, the lack of standardised protocols presents challenges, often necessitating additional extraction and analytical procedures using techniques such as LC-MS/MS or ELISA. Recent advancements in satellite-based remote sensing have been enabled large-scale, near real-time monitoring of algal blooms, particularly through the detection of pigment indicators such as chlorophyll-a. Despite their broad coverage, these systems are limited in their ability to differentiate species or directly detect toxin concentrations. Emerging technologies-including automated imaging flow cytometry, molecular detection tools, and drone-based monitoring systems-are being explored to enhance surveillance capabilities. Additionally, community-driven approaches such as citizen science initiatives, social media data analysis, and municipal reporting systems (e.g., 311 services) offer cost-effective and innovative supplementary monitoring strategies. Collectively, these approaches aim to address existing limitations in accurately characterising

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HAB dynamics and associated health risks (Lim et al., 2023).

4.1. Mechanism of Aerosolized, Transport, and Exposure for HAB Toxins

Harmful algal blooms (HABs) can generate toxins that become aerosolised and subsequently transported through atmospheric processes, leading to human exposure primarily via inhalation. The principal mechanism of aerosol generation involves bubble formation due to wind and wave action, followed by bubble rise and bursting at the air-water interface, which releases toxin-containing droplets into the atmosphere. These spray aerosols may originate from marine (sea spray aerosol, SSA), freshwater (lake spray aerosol, LSA), or estuarine environments and can contain intact algal cells, dissolved toxins, or cellular fragments. The nature of aerosolization varies depending on species and water chemistry; for instance, brevetoxins from Karenia brevis are released during cell lysis, whereas cyanotoxins may be emitted during cellular stress or senescence. Once aerosolised, toxins may become significantly enriched relative to their concentrations in water through bubble scavenging processes. Particle size plays a critical role in determining respiratory deposition, with larger particles depositing in the upper airways and smaller particles-particularly ultrafine and accumulation-mode particles-penetrating deeper into the lungs. The transport of these aerosols is governed by both particles' characteristics and meteorological conditions, with documented cases of toxin dispersion extending several kilometres inland. While deposition predominantly occurs in the nasal and tracheobronchial region, studies have identified microcystins in nasal swabs following recreational exposure, indicating potential internal exposure influenced by individual susceptibility and environmental conditions (Lim et al., 2023).

4.2. Human Health Effects and Mechanisms

Inhalation represents the primary pathway for human exposure to aerosolised HAB toxins, which are associated with a range of respiratory and systemic health effects. One of the most extensively studied HAB species is Karenia brevis, which produces neurotoxic brevetoxins. Exposure to these toxins has been linked to acute respiratory symptoms-including coughing, wheezing, throat irritation, and nasal congestion-in both healthy individuals and those with pre-existing respiratory conditions such as asthma. Epidemiological studies have reported increased emergency room visits and hospital admissions for respiratory illness during red tide events in Florida, particularly among costal populations. Individuals with asthma are especially vulnerable, as even short-term exposure can result in significant declines in lung function and prolonged exacerbation of symptoms. In addition to the respiratory effects, brevetoxins have been associated with systemic symptoms such as headaches and neurological disturbance. Other HAB species, including Ostreopsis spp., produced potent toxins (e.g., ovatoxins) that have caused outbreaks of respiratory and dermatological illnesses in Mediterranean coastal regions. These events have been characterised by symptoms such as fever, cough, rhinitis, and skin irritation. Although most symptoms are transient and resolved within hours to days, the long-term health consequences remain insufficiently understood. There is growing concern regarding chronic or repeated low-level exposure, particularly among population residing near bloom-prone water bodies or occupationally exposed groups. Variability in health outcomes is influenced by factors such as toxin type, concentration, individual susceptibility, and pre-existing health conditions, underscoring the need for further research on exposure thresholds, dose-response relationships, and potential interactions with other airborne pollutants (Lim et al., 2023).

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4.3. SRS Application in the Atmosphere, Ecosystem and its Application in Terrestrial Ecosystem

Satellite remote sensing (SRS) plays a crucial role in atmospheric monitoring by providing high-resolution, global-scale datasets essential for understanding climate processes. A primary application of SRS is the detection and quantification of greenhouse gases (GHGs), particularly methane (CH4) and carbon dioxide (CO2), which are major contributors to global warming. Instruments aboard platforms such as TanSat, the Orbiting Carbon Observatory (OCO), and the Greenhouse Gases Observing Satellite (GOSAT) have enabled precise mapping of atmospheric CO2 and CH4 concentrations across spatial and temporal scales. Additionally, sensors such as MODIS, AVHRR, and CALIPSO facilitate monitoring of aerosols and clouds, improving understanding of radiative forcing, cloud-aerosol interactions, and associated climate feedback mechanisms. These datasets are indispensable for climate modelling, tracking atmospheric composition changes, and validating emission mitigation strategies (Zhao et al., 2023). SRS has also transformed ecosystem monitoring by enabling comprehensive analysis of interactions among terrestrial, marine, and atmospheric systems. In marine environments, it is widely used to assess sea surface temperature (SST), ocean circulation, sea level variations, and phytoplankton productivity. Satellite-derived chlorophyll-a concentrations, obtained from platforms such as MODIS and SeaWiFS, serve as indicators of marine ecosystem health and carbon cycling. Observed SST trends have revealed significant warming patterns associated with phenomena such as El Nino and coral bleaching events (Abbaszadeh M et al., 2026).

In freshwater and terrestrial ecosystems, SRS supports the evaluation of vegetation health, water body dynamics, snow cover, and the occurrence of hydrological extremes such as floods and droughts. These observations contribute to assessment of ecosystem services, biodiversity conservation, and the impacts of climate variability (Zhao et al., 2023). Remote sensing (RS) further provides essential capabilities for monitoring vegetation dynamics, carbon fluxes, land use and land cover change (LULCC), and hydrological hazards in terrestrial environments. Data from satellite systems such as Landsat, MODIS, and Sentinel enable detailed tracking of deforestation, urban expansion, agricultural transformation, and desertification. These measurements are critical for assessing the impact of human activities and climate change on land systems and carbon emissions. Moreover, SRS facilitates the estimation of solar-induced chlorophyll fluorescence (SIF) and gross primary productivity (GPP), both of which are fundamental indicators of photosynthetic activity and ecosystem productivity. Water resource management is also supported through the assessment of soil moisture, snow and ice extent, and terrestrial water storage using missions such as SMAP, GRACE, and GPM. The application of remote sensing indices and algorithms enhance the detection and assessment of droughts and floods, thereby improving mitigation and adaptation strategies in response to climate-driven hydrological variability. Overall, SRS enables timely, accurate, and spatially comprehensive monitoring of terrestrial ecosystems, supporting climate policy development and sustainable land management (Zhao et al., 2023).

5. Conclusion

Atmospheric radionuclide surveillance requires an understanding of both radiological properties and the physical behavior of aerosols that control transport, deposition, resuspension, and exposure. Conventional environmental sampling remains fundamental because it provides direct analytical evidence, but its spatial and temporal limitations create a need for complementary monitoring technologies. Spectroscopic and remote sensing approaches can broaden

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environmental coverage, while sensor networks can improve measurement frequency. Artificial intelligence and machine learning provide an additional opportunity to integrate these increasingly complex datasets. Recent PM_{10} forecasting demonstrates that XGBoost, CatBoost, ANN, LSTM, Bi-LSTM, and ensemble approaches can identify nonlinear relationships, accommodate temporal patterns, and generate location-specific 24 h atmospheric predictions. However, these PM_{10} results should be viewed as a transferable computational framework rather than direct evidence of radionuclide forecasting capability. Future radionuclide research should therefore validate such approaches using radiological measurements and integrate them with meteorological observations, aerosol properties, SRS data, and ground-based monitoring. A combined framework of physical understanding, direct measurement, remote observation, and AI-assisted forecasting could provide a more responsive approach to environmental surveillance, exposure assessment, and early warning.

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