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GIS-Enhanced Environmental Risk Assessment Model for High-Priority Industrial Redevelopment Sites

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Abstract

Redeveloping high-priority industrial sites requires a robust understanding of environmental risks to ensure safe land reuse, regulatory compliance, and sustainable urban planning. This study presents a GIS-Enhanced Environmental Risk Assessment Model designed to integrate spatial analytics, environmental datasets, and contaminant-specific indicators to improve the evaluation of legacy pollution and potential human–ecosystem exposure pathways. The model synthesizes multi-layer geospatial information, including soil chemistry, hydrogeology, groundwater flow patterns, historical land-use records, atmospheric dispersion parameters, and proximity to sensitive receptors such as residential zones, schools, wetlands, and surface water bodies. Through the use of spatial interpolation, contamination hotspot mapping, and weighted overlay analysis, the model generates a comprehensive risk index that supports evidence-based prioritization of remediation interventions across industrial redevelopment sites. The proposed framework incorporates environmental thresholds, regulatory standards, and EPA-recommended screening levels, enabling planners and regulatory agencies to identify areas that exceed acceptable contaminant limits. GIS-based spatial modeling further helps visualize pollutant migration pathways, delineate zones of elevated exposure potential, and simulate alternative redevelopment scenarios under varying remediation strategies. The integration of remote sensing datasets enhances temporal monitoring of site conditions, enabling early detection of land-surface changes, vegetation stress patterns, and hydrological alterations that may signal evolving contamination risks. A decision-support module embedded in the model provides a transparent methodology for ranking redevelopment sites based on environmental severity, socio-economic implications, and projected remediation costs. Application of the model to representative industrial brownfield sites demonstrates its ability to improve assessment accuracy, reduce uncertainties associated with heterogeneous contamination, and enhance stakeholder engagement through intuitive spatial visualizations. The results underscore the critical role of GIS-driven approaches in modern environmental management and sustainable land-use planning. By offering a scalable, data-driven assessment tool, the study contributes to improved environmental stewardship and promotes safer redevelopment of industrial zones affected by legacy pollution. The GIS-Enhanced Environmental Risk Assessment Model ultimately strengthens regulatory decision-making, supports community health protection, and advances the transition toward resilient, sustainable, and economically productive post-industrial landscapes.

Keywords: GIS, Environmental Risk Assessment, Industrial Redevelopment, Brownfields, Geospatial Modeling, Contamination Hotspot Mapping, Exposure Pathways, Spatial Analysis, Remediation Planning, Decision-Support Tools

1. Introduction

The redevelopment of high-priority industrial sites presents complex challenges that stem from decades of intensive production, inadequate waste management practices, and poorly documented historical land uses that have left behind significant environmental legacies. These sites often contain heterogeneous contamination distributed across soil, groundwater, and surface water systems, creating substantial uncertainties for planners, environmental managers, and regulatory agencies seeking to reclaim them for safe and productive use (Alibakhshi, *et al*., 2017, Zhang, et akl., 2013). Traditional assessment methods, while useful, frequently fall short in capturing the spatial variability, multidimensional exposure pathways, and dynamic environmental conditions that influence risk levels across contaminated landscapes.

As urbanization intensifies and the demand for land suitable for housing, commercial activities, and green infrastructure increases, the need for reliable, data-driven approaches to evaluate environmental hazards has become more urgent.

A GIS-enhanced environmental risk assessment model provides a transformative avenue for addressing these challenges by integrating diverse spatial datasets, analytical tools, and visualizations capable of revealing complex contamination patterns that would otherwise remain undetected. Through its ability to layer historical land-use records, hydrogeological information, soil chemistry data, proximity to sensitive receptors, and contamination transport pathways, GIS offers a comprehensive spatial perspective essential for modern environmental planning. The capacity to perform spatial interpolation, hotspot detection, multi-criteria evaluation, and predictive modeling enables stakeholders to understand not only where contaminants are located but also how they behave over time and how they may affect human health and ecological systems (Manfreda, *et al*., 2018, Sims & Colloff, 2012).

Incorporating advanced geospatial tools into environmental risk assessment supports transparent, evidence-based decision-making, reduces uncertainties in redevelopment planning, and enhances regulatory compliance by enabling comparisons with environmental thresholds and remediation standards. Moreover, GIS-driven analyses facilitate targeted remediation, optimized resource allocation, and the prioritization of sites that pose the greatest risks, thereby improving both economic and environmental outcomes. As aging industrial corridors become focal points for revitalization, the integration of GIS in risk assessment is no longer optional but essential for ensuring that redevelopment activities are sustainable, resilient, and aligned with long-term urban planning objectives (Buma & Livneh, 2017, Zhai, Yue & Zhang, 2016).

2. Methodology

A GIS-Enhanced Environmental Risk Assessment Model (GERAM) for high-priority industrial redevelopment sites can be implemented as a mixed-methods, spatially explicit risk-ranking workflow that integrates (i) geospatial screening and exposure pathway logic, (ii) remote-sensing and in-situ monitoring evidence, and (iii) predictive analytics with decision rules that support redevelopment prioritization, remediation targeting, and long-term monitoring. The study begins by defining the decision unit as a "site polygon" (redevelopment parcel boundary) and its area of influence (buffered zone aligned with plausible exposure pathways such as groundwater flow direction, drainage connectivity, and prevailing wind sectors). A base geodatabase is built by compiling satellite/remote-sensing products (land cover/imperviousness, vegetation stress indices, surface moisture proxies), hydro-climatic layers (DEM, slope, flow accumulation, drainage density), land use and sensitive receptors (schools, clinics, residences), and regulatory/operational attributes (past industrial processes, chemical handling, treatment units) to capture credible hazard sources and process-linked accident potential (Gharehbaghi & Scott-Young, 2018; Thakur *et al*., 2017; Afolabi *et al*., 2020b). Historical site use is reconstructed from planning records, imagery time series, and field reconnaissance to identify legacy hotspots, likely contaminant groups, and potential "secondary sources" such as sludge handling footprints, drainage outfalls, and chlorination/disinfection infrastructure that can elevate acute and chronic risk in water-adjacent sites (Afolabi *et al*., 2020a; Afolabi *et al*., 2020b).

Primary data collection follows a tiered field protocol: rapid screening first (walkover, GPS-referenced observations, photo logs, evidence of stained soils, stressed vegetation, drainage conditions), then confirmatory sampling guided by a conceptual site model (CSM) that links sources–pathways–receptors. Sampling locations are selected using GIS stratification (hotspot zones, upgradient/background controls, drainage convergence points, downwind/down-gradient receptors) and optimized to reduce spatial bias and improve inference. Where water and sanitation infrastructure or interventions influence environmental conditions, in-situ sensors and targeted spot measurements are incorporated to improve temporal coverage and reduce uncertainty in exposure proxies (Andres *et al*., 2018). If wastewater treatment or layered soil treatment systems are relevant to site reuse planning, design/operational variables are captured as covariates because they can modify contaminant mobility and attenuation (An *et al*., 2016). For sites with suspected groundwater impacts, intrinsic vulnerability descriptors (depth to water table proxies, permeability surrogates, topographic wetness index, proximity to recharge features) are derived in GIS for subsequent modeling, consistent with GIS-supported environmental assessment practice (Gharehbaghi & Scott-Young, 2018; Naghibi *et al*., 2016).

To convert heterogeneous evidence into actionable risk, the model computes three coupled indices for each site: a Hazard Potential Index (HPI), an Exposure Pathway Index (EPI), and a Receptor Sensitivity Index (RSI). HPI is constructed from legacy process indicators (e.g., chemical sludge conditioning/dewatering residues and polymer usage footprints) and operational hazard attributes (e.g., chlorination/disinfection unit proximity, storage, historical releases) that reflect both contamination likelihood and process-safety severity (Afolabi *et al*., 2020a; Afolabi *et al*., 2020b). EPI is generated from spatial pathway variables (runoff connectivity, flood susceptibility, groundwater flow potential, distance-to-surface-water, soil/land cover permeability proxies, and wind exposure corridors), supported by remote-sensing indicators that can act as early signals of ecological stress or hydrological transitions (Alibakhshi *et al*., 2017; Buma & Livneh, 2017; Thakur *et al*., 2017). RSI captures receptor density and vulnerability (population, sensitive land uses, ecosystem services proxies), and is adjusted using planning context of industrial regeneration to reflect redevelopment pressure and land-use change risk (Boriana, 2017; Cheng *et al*., 2011). Each index is normalized (0–1), quality-flagged, and weighted using a transparent multi-criteria logic (expert scoring plus sensitivity testing) to produce a Composite Environmental Risk Score (CERS).

Predictive analytics is then used to (a) estimate risk surfaces within and around each site, and (b) classify sites into priority tiers. A supervised learning layer is trained where labels exist (e.g., known exceedances, confirmed contamination classes, remediation history), otherwise semi-supervised clustering is applied to identify latent site types. Model candidates include Random Forest or ensemble learners suitable for non-linear interactions and mixed data types, reflecting best practice in contamination risk mapping and ensemble modeling for environmental prediction (Barzegar *et al*., 2018; Rodriguez-Galiano *et al*., 2014; Ransom *et al*., 2017). Feature engineering combines remote-sensing time-series summaries (trend, seasonality, abrupt change metrics) with GIS covariates and field chemistry/physical measurements. Where real-time or high-frequency data streams are available (sensors, IoT deployments), an ingestion pipeline is used to append fresh observations to the geodatabase and enable rolling updates of risk scores, drawing on IoT-big data forecasting concepts (Ahmed, 2017; Zhai *et al*., 2016). To ensure scalable processing and reproducible runs across many sites, the workflow is implemented as modular services (data ingestion, preprocessing, modeling, scoring, mapping) with automated constraint checks (e.g., missing-data thresholds, coordinate validity, range constraints). Algorithmic constraint satisfaction concepts are used to enforce rule consistency (e.g., a site cannot be assigned "low exposure" if receptor density and pathway connectivity exceed set bounds), and cloud-style scaling logic is applied to allocate compute for larger cities or national inventories of brownfields (Ahmed *et al*., 2019; Ahmed *et al*., 2020).

Model performance and credibility are evaluated through spatial cross-validation (e.g., block CV to limit spatial leakage), confusion matrices for tier classification, and error/uncertainty reporting for continuous risk outputs. Ground-truth validation uses withheld samples and independent observations (e.g., targeted resampling, confirmatory laboratory tests, or regulator datasets where available). The study conducts sensitivity and uncertainty analysis by varying index weights and testing how rankings shift, and it reports stability statistics (rank correlation and tier-flip rates) so decision makers can see whether a site's priority is robust or weight-dependent. Finally, outputs are operationalized into GIS decision products: (i) a site-level risk register, (ii) hotspot maps (risk rasters and pathway corridors), (iii) recommended sampling and remediation focus zones, and (iv) a monitoring plan that specifies indicators, sensor placement logic, and update frequency. The redevelopment recommendation step integrates risk tiering with land-use suitability planning to support phased redevelopment that aligns mitigation intensity with risk magnitude, consistent with integrative brownfield planning approaches (Cheng *et al*., 2011; Cappuyns & Kessen, 2014).

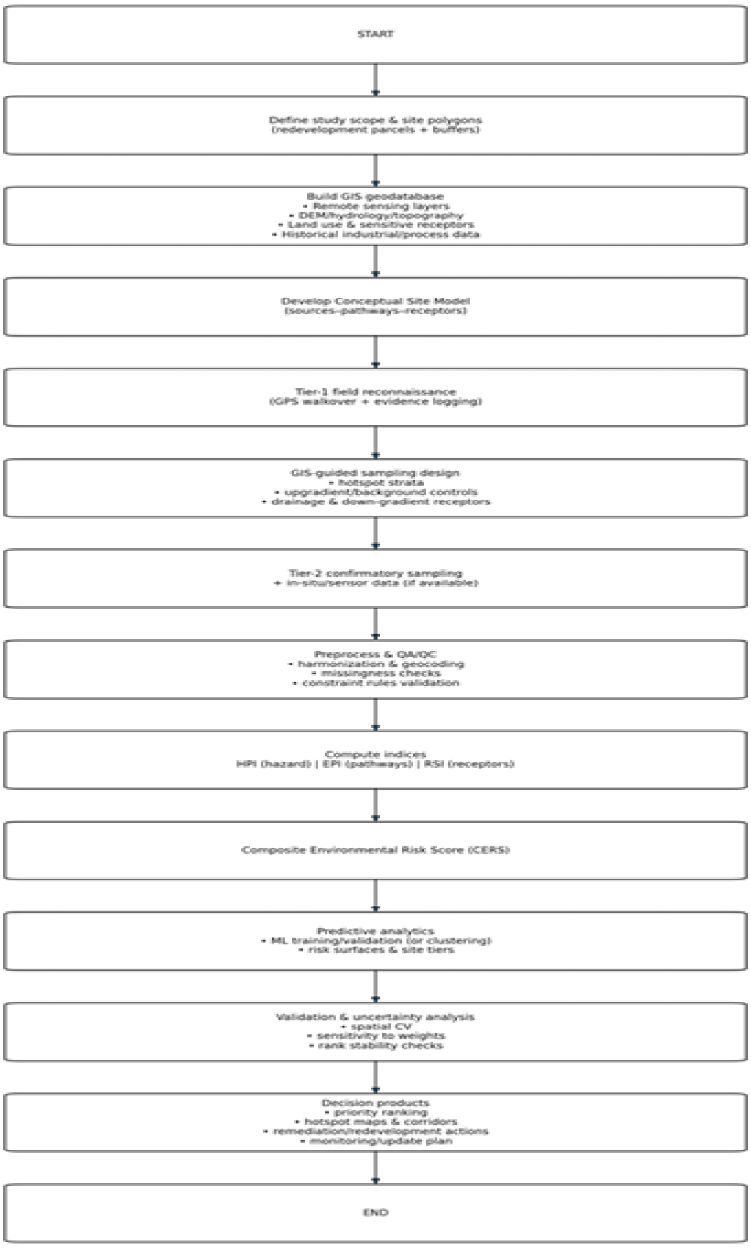

Fig 1: Flowchart of the study methodology

3. Background and Problem Statement

The redevelopment of high-priority industrial sites presents a uniquely complex set of challenges rooted in historical land-use practices, extensive pollution legacies, and the increasing demand for safe and sustainable land reuse in rapidly expanding urban regions. Many industrial sites were developed during periods when environmental regulations were limited or nonexistent, resulting in decades of unmonitored emissions, improper waste disposal, accidental chemical releases, and poorly documented operational processes. These activities have left behind contaminant mixtures in soil, groundwater, sediments, and surrounding ecosystems. As these areas become prime targets for urban renewal, economic revitalization, and infrastructure expansion, the need for accurate and reliable environmental risk assessment has become more critical than ever. However, traditional assessment frameworks often fall short of adequately characterizing the spatial and temporal complexity of contamination, thereby hindering effective remediation planning and exposing communities to potential long-term risks (Schultz & Engman, 2012, Sorooshian, *et al*., 2014).

Conventional environmental assessment methods typically rely on point-based sampling, laboratory analyses, and expert interpretation to identify contaminants and evaluate risks. While these approaches provide valuable site-specific information, they are fundamentally limited in capturing the heterogeneous nature of contamination across large and dynamic industrial landscapes. Contaminants rarely occur uniformly; instead, they form irregular plumes influenced by soil structure, hydrogeology, stormwater dynamics, depth to groundwater, and decades of variable industrial activity. The reliance on sparse sampling points means that much of the subsurface remains uncharacterized, often leading to incomplete understanding of pollutant distribution (Thakur, Singh & Ekanthalu, 2017). This gap introduces significant uncertainties, resulting in either overly conservative remediation strategies that inflate costs or insufficient interventions that leave residual risks unaddressed. Moreover, traditional assessments often struggle to identify emerging contaminants or interactions among multiple pollutants that may enhance toxicity or mobility.

Another major challenge lies in the fact that high-priority industrial redevelopment sites typically exhibit layered contamination histories, where pollutants from different industrial eras overlap spatially and chemically. These overlapping contaminants make it difficult to isolate exposure pathways or predict potential migration patterns. Soil properties, groundwater flow, seasonal variability, and infrastructural alterations further influence contaminant behavior, requiring analytical methods capable of integrating multiple environmental processes simultaneously. Traditional assessment techniques, however, lack the computational and spatial modeling capacity needed to predict contaminant transport or understand how environmental changes such as increased rainfall intensity due to climate change may influence pollutant mobility over time (Andres, *et al*., 2018, Turczynowicz, Pisaniello & Williamson, 2012).

Regulatory requirements add another layer of complexity to environmental assessment for redevelopment projects. Agencies such as the U.S. Environmental Protection Agency (EPA) mandate comprehensive evaluations of pollutant concentrations, exposure pathways, ecological risks, and human health implications. Many jurisdictions require alignment with screening thresholds, risk-based corrective actions, and evidence-backed remediation plans. Meeting these requirements demands accuracy, transparency, and reproducibility, yet traditional assessment tools often produce static, fragmented datasets that are difficult for regulators and stakeholders to interpret. Regulatory frameworks increasingly emphasize cumulative risk assessment, cross-media interactions, and long-term stewardship all of which require integrated, spatially explicit data that traditional methods are not designed to produce. Inadequate or nonstandardized assessment approaches may lead to long approval timelines, rejection of redevelopment proposals, or costly re-evaluations after remediation has begun. Figure 2 shows figure of GIS in Disaster Management presented by Paul, *et al*., 2020.

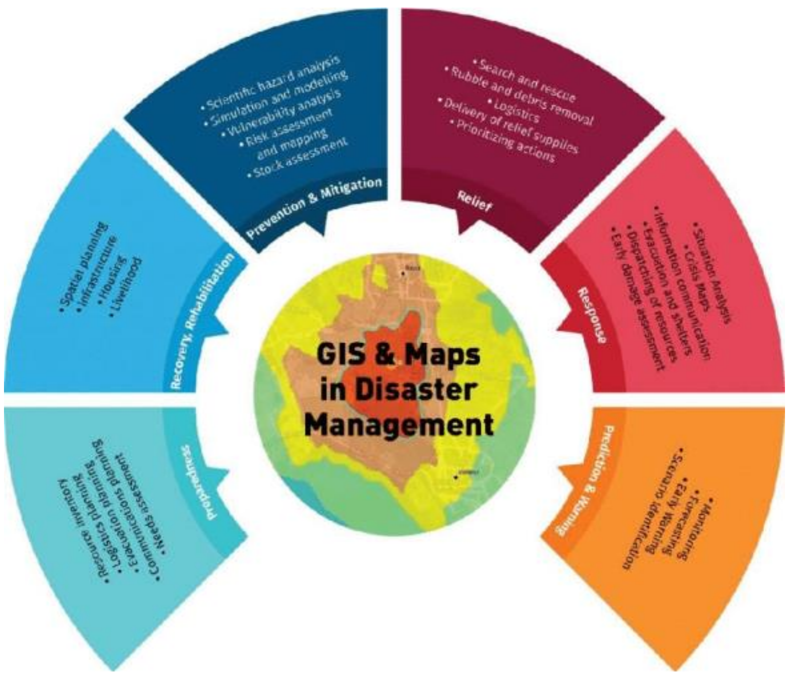

Fig 2: GIS in Disaster Management (Paul, *et al*., 2020).

In addition to regulatory pressures, there are significant gaps in current evaluation methods that hinder effective decision-making across contaminated industrial sites. Many assessment frameworks rely heavily on historical documentation, yet industrial records are frequently incomplete, inaccurate, or unavailable. This lack of reliable baseline information forces practitioners to make assumptions about contaminant sources, magnitudes, and behavior, increasing the risk of misclassification and misinterpretation. In many cases, early assessments fail to capture the full breadth of contamination because initial sampling strategies are designed without the benefit of spatial intelligence (McAlary, Provoost & Dawson, 2010, Provoost, *et al*., 2013). This oversight results in remediation strategies that address only part of the problem, allowing contaminants to persist or migrate into newly redeveloped areas, thereby posing risks to future occupants and undermining public confidence in the redevelopment process.

Furthermore, current assessment practices often lack the capacity to integrate advances in environmental monitoring technologies such as remote sensing, real-time sensors, and predictive modeling tools. These technologies generate extensive datasets that could significantly improve the precision of risk evaluations, yet traditional methodologies provide no structured mechanism for incorporating them. The absence of integrated systems means valuable information about vegetation stress, land-surface anomalies, hydrological changes, or atmospheric emissions remains underutilized. Without holistic tools capable of merging these datasets with ground-based measurements and regulatory thresholds, decision-makers are left with fragmented insights rather than comprehensive risk profiles (Roghani, 2018, Wang, Unger & Parker, 2014).

Public engagement and transparency also suffer under conventional assessment models. Risk communication relies heavily on technical reports, tables, and nonvisual data that are difficult for nonexperts to interpret. As industrial redevelopment often occurs in densely populated, low-income, or historically marginalized communities, there is a critical need for assessment tools that can communicate risks clearly and inclusively (Derycke, *et al*., 2018, Kulawiak & Lubniewski, 2014). Traditional methods fail to offer intuitive visualizations, spatial comparisons, or scenario simulations that could help stakeholders understand potential environmental and health outcomes. This gap contributes to mistrust, resistance to redevelopment initiatives, and delays in achieving consensus on remediation strategies. Figure 3 shows schematic illustrating methodology of environmental impact assessment based on RS, GIS, and landscape analyses presented by Li, *et al*., 2010.

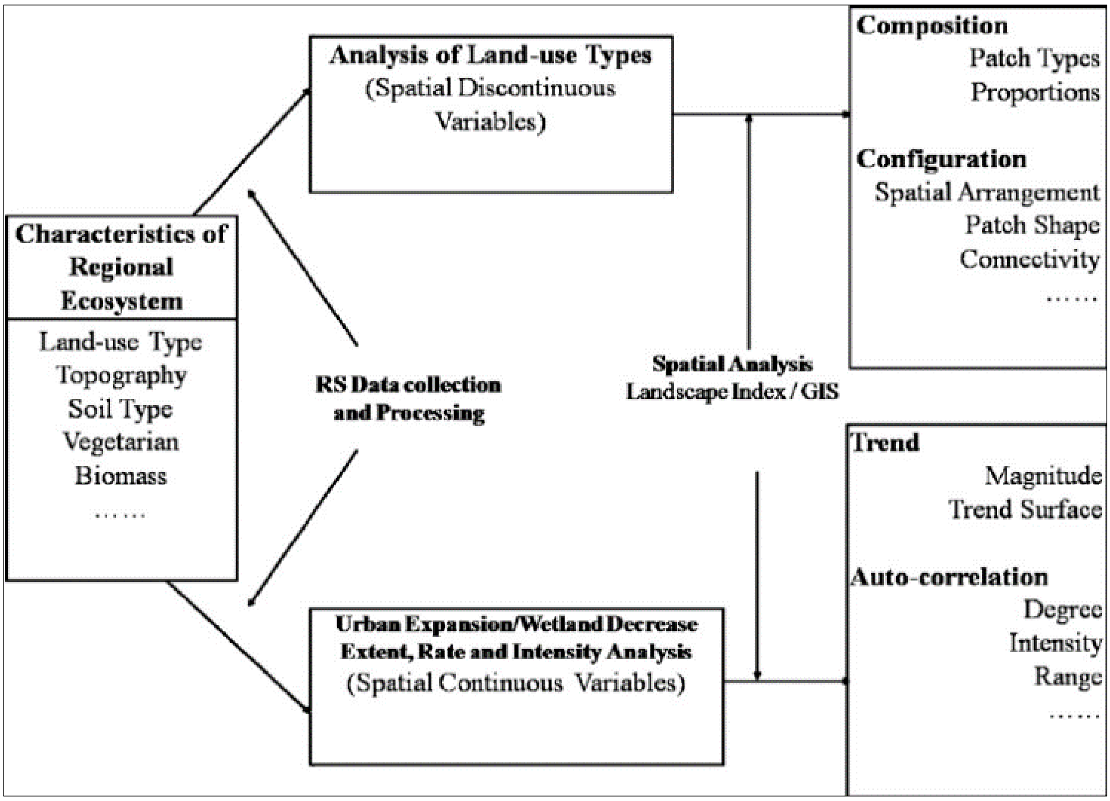

Fig 3: Schematic illustrating methodology of environmental impact assessment based on RS, GIS, and landscape analyses (Li, *et al*., 2010).

The culmination of these challenges underscores the urgent need for advanced geospatial tools capable of transforming environmental risk assessment into a more accurate, transparent, and comprehensive process. Geographic Information Systems (GIS) have emerged as one of the most powerful technologies for addressing the limitations of traditional methods. GIS enables the integration of diverse datasets including soil chemistry, hydrogeology, land use, topography, atmospheric dispersion, and proximity to sensitive receptors into a unified spatial framework. This capability is essential for understanding contamination patterns, modeling pollutant transport, identifying hotspots, and predicting exposure pathways (Hoek, Beelen & Brunekreef, 2011, Levy, 2013). Moreover, GIS supports multi-criteria analysis, allowing practitioners to evaluate environmental, social, economic, and regulatory factors simultaneously.

Despite its potential, GIS is still underutilized in many redevelopment assessment processes, largely due to gaps in technical capacity, lack of standardized protocols, and insufficient awareness among practitioners and policymakers. As redevelopment pressures intensify and environmental liabilities accumulate, the limitations of traditional assessment methods will become increasingly untenable. A GIS-enhanced environmental risk assessment model offers a transformative pathway by enabling spatial intelligence, predictive analytics, transparent communication, and evidence-based decision-making. Its adoption will bridge critical gaps in current evaluation practices and support the safe, sustainable, and equitable redevelopment of high-priority industrial sites (Bowen & Wittneben, 2011, Schaltegger & Csutora, 2012).

4. The Role of GIS in Environmental Risk Assessment

Geographic Information Systems (GIS) have become indispensable tools in modern environmental risk assessment, particularly for high-priority industrial redevelopment sites where contamination is complex, multidimensional, and often poorly documented. The role of GIS in this context extends far beyond simple mapping; it encompasses an integrated analytical framework capable of synthesizing vast quantities of spatial and non-spatial data to reveal contamination patterns, model exposure pathways, and support evidence-based decision-making. As environmental challenges grow more intricate and regulatory expectations become more stringent, GIS provides the technical backbone needed to transition from traditional, fragmented assessment approaches to comprehensive, data-driven models that reflect the true complexity of industrial landscapes (Maas, Schaltegger & Crutzen, 2016, Tang & Luo, 2014).

One of the core strengths of GIS is its capacity for spatial analytics, which enables practitioners to identify relationships, patterns, and trends that cannot be detected through conventional point-based sampling or isolated laboratory results. Contaminants rarely occur in uniform distributions across industrial sites; instead, they form hotspots, gradients, and plumes influenced by soil heterogeneity, groundwater flow, and historical industrial operations. Spatial analytics allows evaluators to interpolate between sampling points, estimate contaminant distribution across unsampled areas, and generate continuous surfaces that visualize both concentration levels and spatial variability (Ascui, 2014, Hartmann, Perego & Young, 2013). By applying kriging, inverse distance weighting, or spline interpolation techniques, GIS generates a more holistic representation of site conditions, drastically reducing uncertainty and revealing hidden contamination zones that could compromise redevelopment plans if overlooked.

GIS data layering further enhances the depth and accuracy of environmental evaluations. Contaminated sites are shaped by multiple interconnected factors geological properties, hydrological processes, land use history, infrastructure networks, ecological sensitivities, and socio-economic contexts. GIS allows all these datasets to be integrated into a multilayered spatial environment where they can be analyzed collectively rather than in isolation. For example, overlaying groundwater direction maps with contaminant plume data helps determine whether pollutants may migrate toward residential areas, wetlands, or critical water wells. Similarly, combining topographic models with stormwater flow patterns reveals how surface runoff might redistribute contaminants after heavy rainfall, a factor increasingly important under climate change conditions (Ascui & Lovell, 2012, Steininger, *et al.*, 2016). This layered integration supports more accurate risk profiling and ensures that remediation strategies are tailored to the unique environmental dynamics of each site.

Remote sensing integration significantly expands the analytical capabilities of GIS in environmental risk assessment. Satellite imagery, aerial photography, LiDAR elevation models, and drone-based monitoring provide continuous, large-scale, and temporally rich datasets that complement ground-based measurements. Remote sensing detects subtle environmental changes such as vegetation stress, abnormal surface temperature patterns, soil moisture anomalies, or surface water fluctuations each of which may signal underlying contamination or hydrological disruptions. When incorporated into GIS, these datasets enhance the early detection of environmental hazards and help validate or refine contamination models (Burritt, Schaltegger & Zvezdov, 2011, Gibassier & Schaltegger, 2015). Remote sensing is particularly valuable for monitoring inaccessible areas or regions where subsurface sampling is limited by cost, safety concerns, or regulatory constraints. Integrating these datasets into GIS allows practitioners to track long-term environmental trends, assess the effectiveness of remediation measures, and identify new risks as redevelopment progresses. Figure 4 shows figure of GIS as a vital tool for Environmental Impact Assessment and Mitigation presented by Gharehbaghi & Scott-Young, 2018.

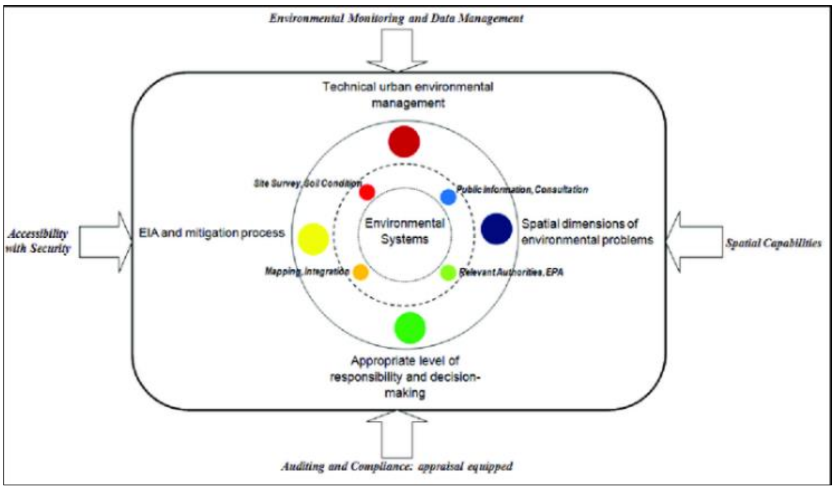

Fig 4: GIS as a vital tool for Environmental Impact Assessment and Mitigation (Gharehbaghi & Scott-Young, 2018).

One of the most critical contributions of GIS to environmental risk assessment is its ability to model and visualize exposure pathways. Contaminants from industrial sites can spread through multiple media air, soil, groundwater, surface water, and biological systems creating complex pathways through which humans and ecological receptors may be exposed. GIS enables the construction of detailed pathway models that illustrate how contaminants are transported, where they accumulate, and which populations or ecosystems are at risk. For instance, modeling groundwater flow and plume migration can identify neighborhoods vulnerable to contaminated well water. Spatial modeling of air dispersion from volatile compounds reveals areas at risk from inhalation exposure (Barzegar, *et al*., 2018, Karandish, Darzi-Naftchali & Asgari, 2017). Mapping soil contamination alongside playgrounds, schools, parks, and residential developments helps quantify potential exposures for sensitive populations such as children and the elderly. These visualization capabilities transform highly technical assessment findings into clear, intuitive maps that regulators, community stakeholders, and decision-makers can easily understand.

Additionally, GIS supports scenario-based planning and predictive modeling, allowing practitioners to assess how environmental conditions might evolve under different land-use changes, climate conditions, or remediation strategies. Predictive models can simulate the impact of installing new stormwater systems, constructing foundations, altering drainage patterns, or modifying industrial infrastructure. This capability helps stakeholders evaluate the consequences of various decisions before implementation, reducing environmental liabilities and ensuring long-term sustainability (Park, *et al*., 2016, Ransom, *et al*., 2017). For example, GIS may reveal how redevelopment activities could inadvertently mobilize contaminants previously immobilized in soil, or how excavation might intersect with a groundwater plume. By testing multiple scenarios, planners can optimize remediation efforts, minimize costs, and ensure that redevelopment aligns with safety and environmental objectives.

GIS also plays a transformative role in improving regulatory compliance and decision-making. Environmental agencies require detailed, transparent, and reproducible evaluations of contamination, exposure pathways, and mitigation plans. GIS provides a standardized framework for storing, analyzing, and presenting environmental data, ensuring consistency and clarity throughout the assessment process. Its ability to integrate regulatory thresholds and screening levels directly into spatial analyses streamlines compliance checks and highlights areas that exceed acceptable limits (Naghibi, Pourghasemi & Dixon, 2016, Rodriguez-Galiano, *et al*., 2014). GIS outputs can be easily shared with regulatory authorities, facilitating faster approvals, reducing discrepancies, and providing a clear audit trail for future reviews. Moreover, GIS-driven analyses align with modern regulatory emphasis on cumulative impacts, cross-media interactions, and climate-resilient planning.

Beyond regulatory functions, GIS enhances community engagement and transparency. Many industrial redevelopment sites are located in densely populated or historically disadvantaged areas where public trust is fragile. Traditional technical reports are often difficult for laypersons to interpret, leading to confusion, mistrust, and resistance to redevelopment initiatives. GIS visualizations such as contamination maps, risk heat zones, and exposure pathway diagrams communicate complex environmental information in a clear, accessible manner. This strengthens public understanding, empowers communities to participate in planning processes, and promotes equitable redevelopment outcomes. Transparent risk communication is essential for building consensus and ensuring that redevelopment plans meet community needs and expectations (Liakos, *et al*., 2018, Singh, Gupta & Mohan, 2014).

Moreover, GIS enables efficient prioritization of sites requiring remediation. High-priority industrial areas typically involve limited funding, tight timelines, and competing redevelopment objectives. GIS-based multi-criteria decision analysis allows stakeholders to evaluate sites based on contamination severity, risk levels, proximity to sensitive populations, potential economic value, ecological considerations, and remediation feasibility. This systematic approach ensures that resources are allocated where they will have the greatest environmental and social impact. It also helps avoid inefficient, politically driven, or ad hoc decision-making processes that may overlook critical scientific evidence (Ahmed, 2017, Karpatne, *et al*., 2018).

In summary, the role of GIS in environmental risk assessment for industrial redevelopment sites is both foundational and transformative. Its capabilities in spatial analytics, data layering, remote sensing integration, exposure pathway visualization, and predictive modeling significantly enhance the precision, comprehensiveness, and transparency of environmental evaluations. By overcoming the limitations of traditional assessment methods, GIS provides a powerful platform for understanding complex contamination patterns, supporting regulatory compliance, informing community engagement, and guiding sustainable redevelopment. As urban growth accelerates and environmental challenges intensify, GIS-enabled risk assessment models will continue to be essential tools for ensuring that industrial redevelopment proceeds safely, responsibly, and with full consideration of long-term environmental and public health outcomes (Liakos, *et al*., 2018, Singh, Gupta & Mohan, 2014).

5. Model Framework and Components

The framework and components of a GIS-enhanced environmental risk assessment model for high-priority industrial redevelopment sites are grounded in the need for a comprehensive, spatially driven approach capable of integrating complex environmental datasets, contamination indicators, and advanced analytical techniques into a unified decision-support system. This model aims to overcome the limitations of traditional assessment practices by providing an accurate representation of contamination dynamics across multiple media, identifying critical risk zones, and supporting remediation planning through transparent, evidence-based spatial analyses. At its core, the model operates as an interconnected framework composed of structured data inputs, sophisticated geostatistical tools, spatial modeling techniques, and decision-making algorithms that collectively enable a deeper understanding of environmental risks in industrial landscapes (Ahmed, 2017, Karpatne, *et al*., 2018).

A foundational component of the model is the integration of diverse environmental data inputs that reflect the multifaceted nature of contamination at industrial sites. Soil datasets capture information on heavy metals, hydrocarbons, persistent organic pollutants, and other industrial residues that accumulate in the vadose zone. Water datasets include information on groundwater levels, hydraulic gradients, dissolved contaminants, turbidity, pH, and conductivity, providing insight into contaminant mobility and subsurface flow dynamics. Surface water data from nearby rivers, canals, and wetlands help assess potential off-site pollutant migration and ecological impacts (Lemming, 2010, Wang, *et al*., 2017). Air quality datasets, though sometimes overlooked in environmental risk models, play a crucial role in identifying volatile organic compounds, particulate matter, and airborne deposition patterns that may pose inhalation risks to nearby communities. Hydrogeological inputs, such as soil permeability, aquifer characteristics, recharge rates, and geological formations, are essential for modeling contaminant transport pathways and understanding the long-term behavior of pollutants in subsurface environments. These datasets collectively form the environmental foundation of the model, enabling a holistic assessment that reflects real-world contamination complexity.

Equally important are the contamination indicators used to interpret and quantify environmental hazards. These indicators include pollutant concentration levels, toxicity thresholds, regulatory screening limits, bioaccumulation potential, and contaminant persistence in various media. Additional indicators such as redox conditions, organic carbon content, and microbial activity influence contaminant degradation and mobility. GIS allows these indicators to be represented spatially, providing clear visualizations of where risks exceed acceptable thresholds and where conditions may favor or inhibit pollutant transformation. The ability to integrate contamination indicators directly into spatial analyses distinguishes this model from traditional assessment frameworks, which often treat environmental variables independently and lack mechanisms for linking them geographically (An, *et al*., 2016, Mgbeahuruike, 2018).

Spatial interpolation techniques form a critical analytical layer in the GIS-enhanced risk assessment model. Given that contamination sampling is typically limited by cost, time, and logistical constraints, interpolation methods help estimate pollutant concentrations in unsampled areas, producing continuous contaminant surfaces across the site. Techniques such as kriging, inverse distance weighting, radial basis functions, and natural neighbor interpolation allow practitioners to generate approximations that reflect underlying spatial structure. Kriging, in particular, is highly effective for environmental datasets because it incorporates spatial autocorrelation, enabling more accurate predictions and estimates of uncertainty. These interpolated surfaces provide essential insights into contaminant distribution patterns, highlighting gradients, directional trends, and diffuse contamination zones that would be invisible through point-based sampling alone (Hardie & McKinley, 2014, Williamson, 2011). By revealing hidden contamination between sampling locations, spatial interpolation supports more informed decisions about where additional sampling, monitoring, or remediation efforts should be concentrated.

Hotspot mapping represents another crucial component of the model, enabling the identification of areas where contaminants reach unusually high concentrations. Using spatial statistics such as Getis-Ord Gi*, local Moran’s I, and kernel density estimation, GIS can detect clusters of elevated contaminant levels and differentiate them from random variation. Hotspots may correspond to historical industrial discharge points, chemical storage areas, waste disposal sites, pipeline leaks, or zones of concentrated surface runoff. Identifying these zones allows practitioners to prioritize remediation activities, allocate resources more effectively, and reduce potential exposure risks. Hotspot maps also provide visual clarity for regulators and community stakeholders, making it easier to communicate the spatial distribution of environmental hazards and justify decision-making processes (Cappuyns & Kessen, 2014, Williamson, *et al*., 2011).

Another essential element of the model framework is multi-criteria weighted overlay analysis, which allows the integration of multiple environmental, socio-economic, and regulatory factors into a single spatial risk index. This technique enables practitioners to assign weights to different variables based on their relative importance in contributing to environmental risk. For example, areas with high contaminant concentrations, low soil permeability, shallow groundwater, and proximity to residential zones may be assigned higher risk scores. Weighted overlay analysis can incorporate factors such as distance to schools, hospitals, water bodies, and ecological reserves, ensuring that the risk model reflects real-world vulnerabilities and human health considerations (Mitchell, 2012, Sweeney & Kabouris, 2017). The method also accommodates regulatory thresholds, such that areas exceeding screening levels automatically receive higher weight values. By combining diverse datasets into a unified risk surface, the model provides a powerful decision-making tool that reveals where risks are most severe and where interventions will have the greatest impact.

In addition to weighted overlays, the model incorporates geoprocessing tools that support complex spatial analyses and scenario testing. Buffering techniques identify areas within specific distances of sensitive receptors or infrastructure. Network analyses explore how contaminants might travel through drainage systems, sewer networks, or natural hydrological pathways. Hydrological modeling tools simulate how rainfall, infiltration, and surface runoff influence contaminant transport, revealing potential flood-induced mobilization risks and identifying pathways that could channel pollutants into nearby water bodies (Cheng, *et al*., 2011, Herat & Agamuthu, 2012). Temporal modeling capabilities allow analysts to track changes in contamination patterns over time and evaluate whether environmental conditions are improving, worsening, or stabilizing. These components collectively provide a dynamic analytical environment in which contamination behavior can be evaluated not only spatially but also temporally.

The model framework also integrates remote sensing data to enhance spatial accuracy and provide insights into environmental conditions that are difficult to capture through ground sampling alone. High-resolution satellite imagery, drone-based surveys, and LiDAR datasets can reveal vegetation stress patterns, soil discoloration, surface anomalies, and structural changes associated with contamination or subsurface activity. Thermal imagery may detect zones of altered land-surface temperature associated with chemical reactions or groundwater discharge. When incorporated into GIS, these remote sensing datasets improve the spatial resolution of contamination models and support early detection of environmental hazards (Boriana, 2017, Hou & Al-Tabbaa, 2014).

Visualization capabilities are another defining component of the model, transforming complex datasets into intuitive maps, charts, and three-dimensional renderings that support communication among scientists, regulators, and community members. Three-dimensional plume modeling helps illustrate subsurface contamination and migration patterns. Heat maps highlight concentration gradients and risk intensities. Layered maps reveal relationships between contamination, land use, hydrology, and population vulnerabilities. These visual outputs play an important role in stakeholder engagement, making the science behind risk assessment more accessible and transparent (Ferdinand & Yu, 2016, Koop & van Leeuwen, 2017).

Finally, the GIS-enhanced model incorporates a decision-support framework that enables practitioners to evaluate multiple remediation scenarios and their environmental implications. By simulating alternative remediation strategies such as soil excavation, bioremediation, pump-and-treat, or containment GIS can help predict how each approach will influence contaminant levels, risk profiles, and long-term site stability. This ensures that redevelopment plans are grounded in robust scientific analysis and that decision-makers can choose strategies that maximize effectiveness while minimizing costs and environmental disruption (Jayasooriya, 2016, Sayles, 2017).

In totality, the model framework and its components form a comprehensive, integrated system capable of addressing the intricate environmental challenges associated with high-priority industrial redevelopment sites. By combining detailed data inputs, sophisticated geostatistical tools, advanced spatial modeling techniques, and multi-criteria decision-making processes, the GIS-enhanced model offers a powerful approach for evaluating contamination, identifying risk zones, prioritizing remediation, and supporting sustainable land reuse.

6. Case Application to High-Priority Industrial Sites

Applying a GIS-enhanced environmental risk assessment model to high-priority industrial redevelopment sites offers a practical demonstration of how spatial technologies, environmental datasets, and advanced analytical methods converge to support evidence-based decision-making. A case application illustrates the model's capabilities in real-world conditions by examining how contaminated industrial areas can be systematically evaluated, visualized, and prioritized for remediation. The implementation process involves clear site selection criteria, comprehensive spatial data acquisition, geoprocessing workflows, visualization outputs, and the identification of high-risk zones based on contamination intensity and exposure pathways. Through this demonstration, the value of GIS in transforming complex environmental assessments into actionable insights becomes evident (Kato, 2010, Meerow & Newell, 2017).

The first step in the case application involves selecting suitable high-priority industrial sites. Site selection criteria typically include the presence of documented or suspected contamination, historical records of intensive industrial operations, proximity to vulnerable communities or ecological receptors, redevelopment pressure from urban planners, and regulatory classification as brownfields or hazardous sites. Additional criteria may include incomplete environmental records, ongoing public health concerns, or evidence of pollutant migration into surrounding environments. The chosen site should reflect the complexity and diversity of contamination challenges associated with legacy industrial landscapes for example, an abandoned manufacturing plant, a former petroleum refinery, or a chemical processing facility (Awe, Akpan & Adekoya, 2017, Osabuohien, 2017). This ensures the assessment model is applied to a context where its full capabilities can be demonstrated.

Following site selection, the next stage involves acquiring spatial data necessary to populate the model. This includes high-resolution satellite imagery to capture current land conditions, historical aerial photos to track past industrial activities, soil and groundwater sampling results, hydrological maps, geological data, topographic surfaces, land use shapefiles, utility networks, and regulatory boundary data. Additional datasets may include remote sensing-derived vegetation indices, land surface temperature models, soil moisture layers, and atmospheric deposition maps, all of which help characterize environmental conditions at multiple scales. Ground-truthing through field surveys and GPS-referenced sampling enhances data accuracy. Each dataset is georeferenced and standardized to ensure consistency across the GIS environment, enabling seamless integration into the risk assessment model (Akpan, Awe & Idowu, 2019, Ogundipe, *et al*., 2019).

Once the datasets are acquired, the model begins processing the information using a series of geospatial workflows. Soil contaminant concentrations are interpolated using kriging or inverse distance weighting to create continuous surfaces that depict pollutant distributions across the site. Groundwater sampling points are combined with hydrogeological layers to model flow directions and contaminant migration pathways. Land use and proximity analyses identify sensitive receptors such as residential areas, schools, rivers, and wetlands (Awe & Akpan, 2017). Hotspot mapping techniques pinpoint clusters of elevated contamination based on spatial autocorrelation metrics. Each layer contributes to understanding how contaminants are distributed and how they interact with environmental systems. The geoprocessing workflow is iterative, allowing analysts to refine parameters as more data becomes available or inconsistencies are detected.

A critical output of the model is contamination plume visualization, which offers a clear representation of how pollutants extend across soil and groundwater systems. Using 3D visualization tools, analysts can depict contaminant concentrations at various depths, illustrating the vertical and lateral extent of plumes. For example, in a petroleum-contaminated site, benzene or toluene plumes may be shown migrating along groundwater gradients, moving from the central industrial footprint toward adjacent neighborhoods or surface water bodies. These plume models reveal not only the concentration levels but also the direction and velocity of contaminant movement, allowing decision-makers to predict future risks based on environmental conditions and industrial legacies (Akpan, *et al*., 2017, Oni, *et al*., 2018). By animating plume progression over time, the model highlights how environmental changes, such as increased precipitation or changes in groundwater recharge patterns, may accelerate contaminant mobility.

Beyond plume visualization, the model generates multiple layers of analytical outputs that contribute to a comprehensive understanding of site-specific risks. Hotspot maps reveal contamination clusters that demand immediate attention or further investigation. Weighted overlay analyses combine factors such as contaminant concentration, distance to receptors, soil permeability, groundwater depth, and ecological sensitivity to produce a composite risk index. This index highlights zones where multiple risk factors coincide, identifying locations that pose the highest environmental and public health threats (Akomea-Agyin & Asante, 2019, Awe, 2017, Osabuohien, 2019). For instance, an area with high heavy metal concentrations, shallow groundwater, and close proximity to a residential district may appear as a red zone on the risk map, indicating severe risk that requires rapid remediation.

Spatial outputs also include buffer analyses that show exposure risks within different radii from the contamination source. A 100-meter buffer around a hotspot may identify risks to industrial workers, while a 500-meter buffer may capture risks to nearby residential areas. These analyses help stakeholders evaluate potential exposure pathways such as inhalation, dermal contact, or ingestion through contaminated water sources. Floodplain overlays further identify how periodic flooding could redistribute contaminants across wider geographic areas, complicating remediation and magnifying risks to downstream ecosystems (Afolabi, *et al*., 2020, Bankole, Nwokediegwu & Okiye, 2020).

Another important component of the case application is the evaluation of site-specific environmental processes. Hydrological modeling tools simulate how stormwater runoff interacts with contaminated soils, revealing pathways through which pollutants may reach surface water bodies. For example, a former chemical plant situated near a river may experience contaminant wash-off during heavy rainfall events, leading to pollutant deposition into aquatic ecosystems. GIS-based flow accumulation and watershed delineation tools highlight how environmental disturbances propagate spatially, enabling planners to design mitigation strategies that address both on-site and off-site risks (Fasasi & Ekechi, 2020, Lawoyin, Nwokediegwu & Gbabo, 2020). These insights are essential for urban redevelopment authorities who must ensure that new construction does not exacerbate contamination problems or endanger public health.

The model also supports scenario testing, enabling analysts to evaluate how different remediation strategies might influence contamination risk. For example, isolating contaminated soil through capping may limit surface exposure but fail to prevent groundwater migration. Alternatively, soil excavation combined with bioremediation may significantly reduce contamination levels but incur higher costs and cause temporary land disturbance. GIS simulations reveal how each approach alters risk profiles across the site, helping stakeholders identify the most effective and sustainable remediation strategy. These predictive capabilities are crucial for balancing environmental, economic, and community interests in redevelopment planning (Fasasi, *et al*., 2020, Lawoyin, Nwokediegwu & Gbabo, 2020).

Throughout the case application, visualization plays a central role in risk communication. Maps depicting contamination intensities, plume movements, risk indices, and remediation scenarios are shared with regulatory agencies, developers, environmental consultants, and community members. These visual outputs provide clarity and transparency, enabling all stakeholders to understand the environmental challenges and the rationale behind recommended interventions. Community engagement meetings benefit greatly from GIS visualization, as residents can clearly see how contamination affects their neighborhoods and what measures are being taken to reduce risks (Ike, *et al*., 2018).

Ultimately, the identification of high-risk zones serves as the culmination of the case application. These zones represent intersections of high contaminant concentration, sensitive receptors, elevated exposure pathways, and regulatory exceedances. By mapping these zones, the GIS-enhanced model provides a concrete basis for prioritizing remediation actions, allocating resources efficiently, and guiding redevelopment plans that prioritize public health and environmental integrity. For example, areas identified as high risk may be designated for intensive remediation, restricted land uses, or environmental monitoring, while lower-risk zones may proceed to redevelopment more quickly. This clear stratification of risk improves decision-making and ensures that redevelopment proceeds safely and sustainably (Nwokediegwu, Bankole & Okiye, 2019, Oshoba, Hammed & Odejobi, 2019).

In conclusion, the case application of the GIS-enhanced environmental risk assessment model demonstrates how spatial technologies transform complex environmental datasets into actionable insights that support safe and effective industrial redevelopment. Through systematic site selection, comprehensive data acquisition, geospatial processing, plume visualization, and risk zone identification, the model provides a robust framework for evaluating contamination dynamics and guiding remediation strategies grounded in scientific evidence.

7. Discussion of Findings and Policy Implications

The discussion of findings from the GIS-enhanced environmental risk assessment model for high-priority industrial redevelopment sites reveals the profound value of integrating spatial analytics, geostatistical modeling, and environmental data into a comprehensive decision-support framework. The model's outputs provide a clearer, more detailed understanding of contamination patterns, exposure pathways, and environmental vulnerabilities than traditional assessment methods, thereby reshaping how redevelopment decisions are made. The interpretation of results highlights both the complexity of legacy pollution and the potential for using geospatial intelligence to guide environmental management, remediation strategies, and policy formulation. These insights carry significant implications not only for environmental protection but also for urban planning, socio-economic development, and community engagement (Fasasi & Ekechi, 2020, Giwah, *et al*., 2020).

Key findings from the model indicate that contamination within industrial redevelopment sites is rarely uniform or predictable. Instead, pollutants form intricate spatial patterns influenced by historical land uses, hydrogeological conditions, and surface processes. The ability of the model to reveal these patterns through spatial interpolation surfaces, plume visualizations, and hotspot mapping demonstrates the inadequacy of traditional sampling techniques that rely on limited data points. The spatial outputs show that contamination often extends far beyond documented areas, sometimes migrating toward residential zones, water bodies, or ecological habitats. These findings underscore the need for environmental managers to adopt spatially informed strategies that reflect the dynamic nature of pollutant movement rather than relying on static or incomplete datasets (Olatunde-Thorpe, *et al*., 2020, Oshoba, *et al*., 2020).

The interpretation of model results also emphasizes the importance of understanding contaminant transport pathways. Groundwater flow modeling reveals how pollutants travel across subsurface environments, sometimes bypassing physical barriers or crossing property boundaries. Surface runoff analyses show how rainfall events can rapidly redistribute contaminants across previously unaffected areas, particularly in sites with compromised drainage systems. These insights inform targeted remediation actions, helping managers identify not only where contamination currently exists but where it is likely to spread in the future. This predictive capability is essential for preventing long-term environmental degradation and avoiding costly remediation failures (Aifuwa, *et al*., 2020, Bankole, Nwokediegwu & Okiye, 2020).

From a remediation prioritization perspective, the model's ability to generate composite risk indices and identify high-risk zones is particularly valuable. Weighted overlay analyses demonstrate that some areas pose disproportionately high risks because they combine multiple hazardous conditions: elevated contaminant concentrations, shallow groundwater, permeable soils, and close proximity to sensitive receptors such as schools, hospitals, or residential neighborhoods. These areas automatically become priority zones for remediation intervention. In contrast, zones with lower contamination levels or reduced exposure potential may require only minimal mitigation or monitoring (Faseemo, *et al*., 2009). This differential approach ensures that limited remediation resources are allocated efficiently, maximizing public health protection while minimizing unnecessary expenditures.

Urban planning decisions are significantly enhanced by the insights generated from the GIS model. Redevelopment projects often involve transforming derelict industrial spaces into residential, commercial, or mixed-use districts. Without a clear understanding of contamination patterns, redevelopment poses risks to future occupants and could lead to long-term land-use conflicts. The model's spatial outputs help planners identify which areas are safe for redevelopment, which require remediation before construction, and which may be unsuitable for certain land uses altogether. For example, areas directly overlying deep contamination plumes may be unsuitable for housing developments but appropriate for industrial reuse or green buffer zones. Urban planners can incorporate these findings into zoning decisions, infrastructure planning, and environmental compliance strategies, ensuring that redevelopment aligns with sustainability and safety goals.

The findings also highlight important socio-economic implications. Many high-priority industrial sites are located in economically disadvantaged or environmentally overburdened communities that have historically borne the brunt of industrial pollution. The model provides a mechanism for identifying environmental injustices by showing where contamination overlaps with vulnerable populations. By visualizing these intersections, policymakers can design targeted interventions that address both environmental risks and socio-economic disparities. Redevelopment projects informed by these findings can create safer living conditions, stimulate local economies, and support community revitalization efforts. Additionally, areas prioritized for remediation may become catalysts for economic development, attracting investment and generating employment opportunities once environmental hazards are mitigated (Hammed, Oshoba & Ahmed, 2019, Sanusi, *et al*., 2019).

Another critical implication relates to environmental management policies. The model's findings suggest the need for regulatory frameworks that emphasize spatially explicit risk assessment and continuous environmental monitoring. Traditional policies that rely on static contamination maps or periodic sampling may not capture the real-time dynamics of pollutant movement. GIS-based models enable ongoing surveillance, early detection of environmental changes, and rapid response to emerging threats. Policymakers could leverage these capabilities to establish guidelines for mandatory spatial assessments in redevelopment projects, standardized reporting systems for contamination data, and adaptive management strategies that respond to changing environmental conditions. Incorporating GIS into policy frameworks ensures greater precision, transparency, and accountability in environmental decision-making (Fasasi, Adebowale & Nwokediegwu, 2019, Owulade, *et al*., 2019).

Stakeholder engagement emerges as one of the most significant benefits revealed by the model's outputs. Environmental risk communication is often hindered by technical complexity, making it difficult for community members to understand the severity and distribution of risks. The model addresses this challenge by translating complex analytical results into intuitive visual maps and diagrams. These visualizations empower residents, community organizations, and local leaders to participate meaningfully in redevelopment discussions. Seeing contamination plumes, hotspot areas, and risk zones provides clarity that written reports cannot achieve. This transparency builds trust, reduces conflict, and fosters collaborative decision-making between developers, regulators, and affected communities (Ahmed, Odejobi & Oshoba, 2020, Giwah, *et al*., 2020).

The model's findings also support more equitable community engagement. In many redevelopment contexts, marginalized populations lack access to information or decision-making power. By using GIS-generated visualizations in public consultations, planners can ensure that community voices are heard and that redevelopment plans reflect local needs and concerns. This enhances procedural justice and strengthens the legitimacy of redevelopment efforts. Moreover, community-driven insights can help refine model inputs by providing local knowledge about historical industrial activities, flooding patterns, or undocumented pollution sources.

Another policy implication concerns long-term environmental monitoring and adaptive management. The model demonstrates that conditions at industrial sites can change rapidly due to climatic events, construction activities, or hydrological alterations. Policymakers can use these findings to advocate for monitoring systems that integrate GIS, remote sensing, and real-time sensors to track environmental conditions continuously. Such systems ensure that remediation measures remain effective over time and that evolving risks are addressed promptly. Additionally, developers and regulatory agencies can use the model's baseline outputs to evaluate the success of remediation efforts through post-cleanup monitoring (Bayeroju, *et al*., 2019, Fasasi, *et al*., 2019).

Finally, the discussion highlights the broader significance of adopting GIS-enhanced risk assessment models in national and regional planning frameworks. As urbanization accelerates and industrial sites become prime locations for redevelopment, the need for robust environmental assessment tools is more critical than ever. The model's findings demonstrate that GIS provides the spatial intelligence necessary to guide sustainable redevelopment, protect public health, and promote environmental resilience. Integrating these tools into national redevelopment programs, environmental protection policies, and land-use planning guidelines would ensure that future development proceeds in a manner that balances economic growth with environmental stewardship (Afolabi, *et al*., 2020, Fasasi, *et al*., 2020).

In summary, the findings and policy implications of the GIS-enhanced environmental risk assessment model reveal its transformative potential for environmental management, remediation prioritization, urban planning, socio-economic development, and community engagement. The model not only enhances the accuracy and comprehensiveness of contamination assessments but also provides a decision-making framework that aligns environmental protection with sustainable redevelopment and social equity (Ahmed, Odejobi & Oshoba, 2019, Nwokediegwu, Bankole & Okiye, 2019).

8. Conclusion

The GIS-enhanced environmental risk assessment model for high-priority industrial redevelopment sites represents a significant advancement in the way complex contamination challenges are understood, evaluated, and managed. By integrating diverse environmental datasets with sophisticated geospatial analytics, the model provides a comprehensive and spatially explicit understanding of contamination patterns, exposure pathways, and environmental vulnerabilities that traditional assessment methods cannot achieve. This enhanced visibility into the behavior and distribution of pollutants allows environmental managers, urban planners, and policymakers to make more informed decisions that protect public health and support sustainable redevelopment. The model's ability to visualize contamination plumes, identify hotspots, and prioritize high-risk zones ensures that remediation efforts are both targeted and cost-effective, ultimately improving environmental outcomes and reducing long-term liabilities.

One of the most important contributions of the model lies in its capacity to unify soil, water, air, and hydrogeological data into a coherent analytical framework. This integration enables users to evaluate the interactions between different environmental systems and understand how contaminants move across them. The resulting insights support more strategic remediation planning, preventing the oversight of critical risk areas and reducing uncertainties that often hinder redevelopment projects. Additionally, the model enhances transparency and stakeholder engagement by transforming technical data into accessible visual formats that facilitate communication and encourage public participation. This is especially vital in communities historically affected by industrial pollution, where trust and clarity are essential for gaining support for redevelopment initiatives.

The potential of the model to improve remediation outcomes is substantial. Its predictive capabilities allow practitioners to anticipate future contamination risks, assess the impact of environmental changes, and test alternative remediation strategies before implementing them. This forward-looking approach ensures that interventions are not only effective in the present but also resilient to future environmental conditions. Furthermore, the model supports regulatory compliance by providing standardized, reproducible outputs that align with environmental guidelines and risk-based decision-making frameworks.

Looking ahead, future research should focus on enhancing the model's predictive accuracy through the integration of emerging technologies such as machine learning, real-time sensor networks, and advanced remote sensing platforms. These technologies can improve the timeliness and precision of environmental monitoring, allowing for adaptive management strategies in rapidly changing environments. Additionally, expanding the model to incorporate socio-economic indicators would deepen its relevance for equitable redevelopment planning, ensuring that environmental justice considerations are embedded in decision-making processes. As cities continue to pursue sustainable redevelopment, the GIS-enhanced risk assessment model will serve as an essential tool for balancing growth, safety, and environmental stewardship.

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