Spatially Explicit Risk Modeling Framework for Tracking Subsurface Contaminant Migration in Data-Limited Remediation Sites

AZEEZ LAMIDI OLAMIDE[1], OMOLOLA BADMUS[2]
[1]OKK Global Resources Limited, Nigeria
[2]Independent Researcher, USA

Abstract- This study presents a Spatially Explicit Risk Modeling Framework designed to track and predict subsurface contaminant migration in data-limited remediation sites, where sparse monitoring networks, incomplete hydrogeological characterization, and constrained resources often undermine effective decision-making. The framework integrates geospatial analysis, probabilistic risk assessment, and simplified transport modeling to generate spatially resolved risk surfaces that support remediation planning under uncertainty. Rather than relying on dense datasets or computationally intensive simulations, the approach leverages readily available site information, including limited borehole logs, historical land-use records, shallow groundwater observations, and proxy environmental indicators, to construct a defensible representation of contaminant behavior in the subsurface. At the core of the framework is a modular architecture that combines conceptual site modeling with spatial interpolation techniques and Bayesian inference to estimate contaminant plume evolution and associated exposure risks. Uncertainty is explicitly quantified and propagated through the model using scenario-based simulations, allowing practitioners to identify high-risk zones, prioritize sampling locations, and evaluate remedial alternatives with transparent confidence bounds. The spatially explicit structure enables visualization of risk gradients across heterogeneous subsurface conditions, facilitating communication between technical experts, regulators, and community stakeholders. The framework is particularly suited to early-stage site assessment and adaptive management contexts, where rapid screening and iterative refinement are required. By emphasizing scalability and transferability, the model can be applied across diverse contaminated land settings, including abandoned industrial sites, legacy petroleum facilities, and informal waste disposal areas. A hypothetical case application demonstrates how the framework can guide targeted data acquisition, reduce uncertainty over time, and improve the efficiency of remediation strategies despite limited input data. Overall, the proposed Spatially Explicit Risk Modeling Framework offers a practical and robust tool for enhancing subsurface contaminant tracking and risk-informed decision-making in data-constrained environments. It bridges the gap between qualitative conceptual models and data-intensive numerical simulations, supporting more resilient, transparent, and cost-effective remediation outcomes. The framework also aligns with contemporary sustainability and environmental governance objectives by promoting evidence-based prioritization, minimizing unnecessary intrusive investigations, and enabling more equitable allocation of remediation resources in low-capacity settings, thereby strengthening long-term environmental protection and public health safeguards. This approach supports adaptive learning and compliance.

Keywords: Spatial Risk Modeling; Subsurface Contamination; Contaminant Migration; Data-Limited Sites; Geospatial Analysis; Uncertainty Quantification; Remediation Planning

I. INTRODUCTION

Subsurface contaminant migration remains one of the most persistent and complex challenges in environmental management and site remediation. Contaminants released from industrial activities, waste disposal practices, mining operations, and accidental spills often migrate through heterogeneous soil and groundwater systems in ways that are difficult to observe directly. Variability in subsurface properties, coupled with delayed detection and evolving land-use patterns, complicates efforts to accurately delineate contaminant plumes and assess associated risks. These challenges are further amplified in many remediation contexts where monitoring infrastructure is limited, historical records are incomplete, and financial or technical resources constrain comprehensive site characterization (Ike, et al., 2018).

Conventional approaches to modeling subsurface contaminant transport typically rely on deterministic numerical models that demand extensive, high-resolution datasets and detailed hydrogeological parameterization. While such models can offer valuable insights under well-characterized conditions, they are often impractical or unreliable in data-scarce remediation sites. Inadequate spatial coverage of sampling points, uncertainty in boundary conditions, and limited temporal data can lead to oversimplified assumptions or misleading predictions. As a result, remediation decisions based solely on traditional modeling techniques may either underestimate potential risks or require costly, overly conservative interventions that strain available resources (Faseemo, et al., 2009).

In response to these limitations, there is growing recognition of the need for alternative modeling paradigms that explicitly accommodate uncertainty while remaining operational in low-data environments. Risk-informed approaches offer a means of shifting emphasis from precise plume prediction to probabilistic assessment of exposure and impact, allowing decision-makers to focus on areas of greatest concern. However, many existing risk assessment tools lack sufficient spatial resolution to capture the heterogeneous nature of subsurface systems, reducing their effectiveness for site-specific planning and communication (Awe, Akpan & Adekoya, 2017, Osabuohien, 2017).

Spatially explicit risk modeling frameworks address this gap by integrating geospatial analysis with probabilistic reasoning to represent contaminant migration and associated risks across space, even when empirical data are limited. By combining conceptual site understanding, simplified transport representations, and uncertainty-aware analytics, such frameworks enable the generation of spatial risk surfaces that support prioritization, adaptive monitoring, and transparent decision-making. In data-limited remediation sites, these frameworks provide a pragmatic pathway for improving subsurface contaminant tracking, enhancing the robustness of remediation strategies, and aligning environmental management practices with sustainability and public health objectives (Hipsey, et al., 2015, Scheidt, Li & Caers, 2018).

2.1. Methodology

The methodology for developing and applying a Spatially Explicit Risk Modeling Framework for Tracking Subsurface Contaminant Migration in Data-Limited Remediation Sites adopts an integrated, adaptive, and uncertainty-aware research design. The approach is informed by systems-based environmental modeling, probabilistic risk assessment, GIS-based spatial analysis, and data-driven learning concepts drawn from decision support systems, hydrogeology, machine learning, and risk-based environmental management literature. Given the inherent constraints of sparse monitoring data and incomplete site characterization, the methodology prioritizes robustness, transparency, and iterative refinement over deterministic precision.

The process begins with comprehensive data collation from heterogeneous sources, including limited borehole logs, groundwater chemistry records, historical land-use data, regulatory reports, satellite imagery, and regional hydrogeological maps. In line with data-driven environmental frameworks and IoT–big data concepts, both structured and unstructured datasets are harmonized within a GIS environment to establish a unified spatial database. Proxy indicators such as soil type, elevation, drainage density, proximity to suspected sources, and land-use intensity are incorporated to compensate for missing subsurface measurements. Data screening and normalization are performed to assess reliability, remove inconsistencies, and assign confidence weights to datasets based on source quality and temporal relevance.

A conceptual site model is then constructed to define contaminant sources, migration pathways, transport mechanisms, and potential receptors. This conceptualization draws on established hydrogeological and contaminant fate principles, integrating advective flow, dispersion, attenuation, and potential back-diffusion processes. Rather than assuming a single definitive conceptual interpretation, multiple plausible conceptual scenarios are developed to reflect uncertainty in subsurface structure and contaminant behavior, consistent with risk-based and scenario-driven decision support methodologies.

Spatial analysis is conducted by transforming point-based observations into continuous surfaces using interpolation techniques suitable for sparse data environments. Deterministic methods such as inverse distance weighting are applied for initial screening, while geostatistical approaches are selectively employed where spatial autocorrelation can be reasonably inferred. Interpolation uncertainty is quantified and retained as an explicit component of the analysis, ensuring that spatial estimates are treated probabilistically rather than as fixed representations.

Risk quantification is implemented using a probabilistic framework that integrates contaminant presence, migration potential, and exposure likelihood. Key variables are represented as probability distributions informed by available data, literature benchmarks, and expert judgment. Bayesian updating principles are applied to refine parameter distributions as new data are introduced, allowing the framework to learn iteratively. In parallel, scenario-based simulations are executed to propagate alternative conceptual assumptions through the spatial model, generating ensembles of risk outcomes rather than single predictions.

Simplified contaminant transport representations are employed to estimate migration potential across the spatial domain without relying on data-intensive numerical solvers. Transport likelihood is approximated using spatial weighting functions based on inferred hydraulic gradients, terrain-driven flow tendencies, and known attenuation characteristics. These transport indicators are combined with interpolated contaminant probability surfaces and receptor vulnerability layers to generate composite spatial risk indices. The resulting spatial risk surfaces highlight gradients, hotspots, and zones of elevated uncertainty that are critical for decision support.

Model implementation follows an adaptive management logic. Initial risk maps are used to prioritize targeted sampling, monitoring expansion, and remedial intervention planning. As new monitoring data become available, they are assimilated into the spatial database, parameter distributions are updated, and risk surfaces are regenerated. This iterative cycle ensures continuous refinement of understanding while optimizing resource allocation. Model performance is evaluated qualitatively through consistency checks with observed trends and quantitatively where validation data permit.

Throughout the methodology, transparency and traceability are maintained through systematic documentation of assumptions, data sources, uncertainty treatments, and model iterations. The framework is designed to function as a decision-support system rather than a predictive oracle, supporting regulators, practitioners, and stakeholders in making defensible, risk-informed decisions under uncertainty. This methodological structure aligns with contemporary sustainability-oriented remediation policies, adaptive environmental governance, and equitable resource management principles in data-limited contexts.

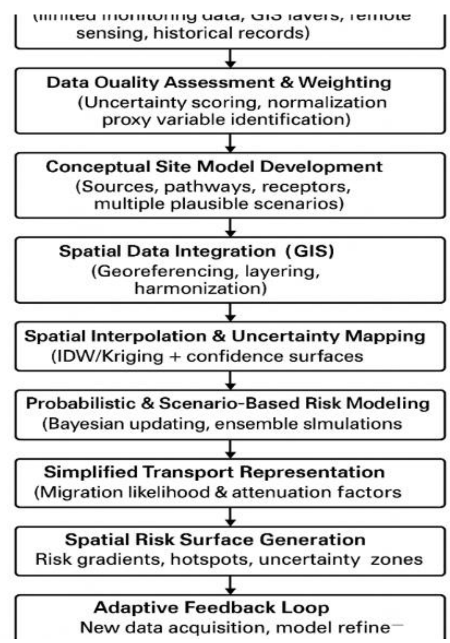

Figure 1: Flowchart of the study methodology

2.2. Conceptual Basis of Subsurface Contaminant Transport

The conceptual basis of subsurface contaminant transport forms the foundation upon which any spatially explicit risk modeling framework must be built, particularly in remediation sites characterized by limited data availability. Subsurface environments are inherently complex systems governed by interacting physical, chemical, and biological processes that control the movement, transformation, and persistence of contaminants. Understanding these processes at a conceptual level is essential for developing models that remain defensible and informative even when detailed site-specific measurements are sparse or uncertain (Awe & Akpan, 2017).

At the core of subsurface contaminant transport are hydrogeological processes that regulate fluid flow through soils and geological formations. Groundwater flow, driven primarily by hydraulic gradients and controlled by permeability and porosity variations, acts as the dominant transport mechanism for many dissolved contaminants. In heterogeneous subsurface settings, contrasts in lithology, stratigraphy, and structural features such as fractures or faults create preferential flow paths that can accelerate contaminant migration or cause unexpected plume divergence. In data-limited sites, these heterogeneities are rarely fully characterized, yet their conceptual representation is critical for anticipating potential contaminant behavior. Simplified depictions of aquifer connectivity, recharge and discharge zones, and vertical hydraulic gradients provide an essential framework for estimating contaminant transport directions and velocities when detailed hydraulic data are unavailable (Akpan, et al., 2017, Oni, et al., 2018).

In addition to advective transport, dispersive and diffusive processes influence plume spreading and dilution. Mechanical dispersion arises from variations in flow velocity at different scales, while molecular diffusion becomes particularly relevant in low-permeability zones such as clays or weathered bedrock. These processes contribute to plume attenuation and persistence, especially where contaminants migrate into less transmissive formations and later back-diffuse into more permeable zones. Conceptually accounting for dispersion and diffusion is vital in data-scarce remediation contexts, as these mechanisms can explain delayed plume stabilization or rebound following remediation efforts, even in the absence of dense monitoring data (Awe, 2017).

Contaminant fate is further shaped by geochemical interactions between contaminants and subsurface media. Sorption processes, including adsorption and ion exchange, can temporarily or permanently retard contaminant movement depending on soil mineralogy, organic matter content, and groundwater chemistry. Redox reactions, biodegradation, and abiotic transformations may alter contaminant speciation, toxicity, and mobility over time. While quantitative parameterization of these reactions is often infeasible in data-limited settings, conceptual recognition of dominant attenuation or transformation mechanisms allows risk models to distinguish between conservative and reactive contaminants. This distinction is critical for spatial risk estimation, as it influences assumptions regarding plume longevity and exposure potential (Deschaine, 2014, Kresic & Mikszewski, 2012).

Understanding contaminant sources and pathways is equally fundamental to the conceptual basis of subsurface transport modeling. Sources may include point releases such as leaking storage tanks, industrial discharge points, landfills, or accidental spills, as well as diffuse sources arising from agricultural practices, atmospheric deposition, or widespread waste disposal. In many legacy sites, source histories are poorly documented, necessitating reliance on indirect evidence such as land-use records, anecdotal information, or spatial patterns in limited sampling data. Conceptual source characterization involves identifying likely release locations, estimating relative source strengths, and distinguishing between active and residual contamination. These elements guide spatial risk modeling by framing where contaminant migration is initiated and how it may evolve over time. Figure 2 shows vertical contaminant transport from a source located in a homogeneous saturated clay, downward to the top presented by Locatelli, et al., 2019.

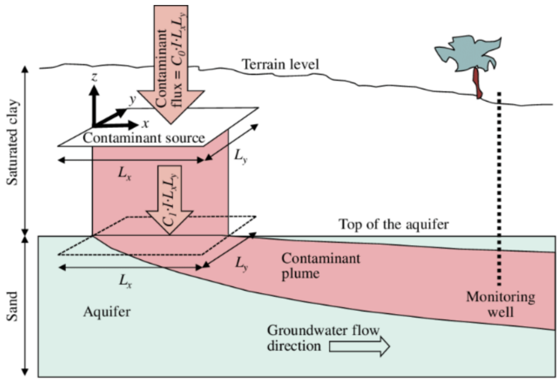

Figure 2: Vertical contaminant transport from a source located in a homogeneous saturated clay, downward to the top (Locatelli, et al., 2019).

Once released, contaminants follow pathways shaped by subsurface structure and hydrological connectivity. Vertical migration through the vadose zone, lateral transport within aquifers, and potential discharge to surface water bodies or extraction wells define the exposure routes of concern. In fractured or karst systems, rapid transport along discrete conduits may dominate, while in porous media, plume evolution may be slower and more diffuse. Conceptual pathway identification enables the spatial delineation of potential receptors, including drinking water supplies, ecosystems, and human populations. In data-limited remediation sites, this pathway-focused understanding supports risk prioritization even when precise plume boundaries cannot be determined (Bello-Dambatta, 2010, Leeson, et al, 2013).

Central to integrating these processes into a spatially explicit risk modeling framework is the development of a robust conceptual site model. The conceptual site model serves as a qualitative yet structured representation of site conditions, synthesizing available information on geology, hydrogeology, contaminant sources, transport mechanisms, and receptors. Rather than functioning as a static diagram, it acts as an evolving hypothesis that guides data interpretation, model development, and decision-making under uncertainty. In contexts where empirical data are sparse, the conceptual site model becomes the primary organizing tool for integrating disparate information sources and expert judgment (Liang, 2018, McGrath, Reid & Tran, 2017).

The role of the conceptual site model in data-limited remediation sites is particularly significant because it provides a transparent basis for simplifying complex systems without obscuring critical risk drivers. By explicitly stating assumptions about subsurface conditions and contaminant behavior, the model clarifies the rationale behind spatial risk estimates and highlights areas of greatest uncertainty. This transparency is essential for ensuring that simplified transport representations used in spatial risk modeling remain credible to regulators, stakeholders, and affected communities (Bello-Dambatta & Javadi, 2010, Felisa, et al., 2015). Figure 3 shows conceptual model for contaminant fate and transport through a homogeneous unsaturated zone presented by Troldborg, 2010.

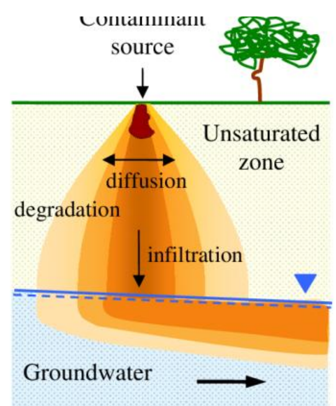

Figure 3: Conceptual model for contaminant fate and transport through a homogeneous unsaturated zone (Troldborg, 2010).

Uncertainty is an inherent feature of subsurface contaminant transport, and its explicit consideration is a defining aspect of risk-informed modeling frameworks. Conceptual site models support uncertainty management by distinguishing between well-supported knowledge and speculative elements, allowing uncertainty to be propagated through spatial analyses in a structured manner. Scenario development, informed by alternative conceptual interpretations of subsurface conditions, enables risk models to explore plausible contaminant migration outcomes rather than relying on a single deterministic prediction. This approach is especially valuable in data-scarce settings, where uncertainty often dominates over parameter precision.

By grounding spatially explicit risk modeling in a sound conceptual understanding of subsurface transport, practitioners can generate meaningful insights despite limited data. The conceptual basis ensures that model outputs reflect the dominant physical and chemical controls on contaminant migration, rather than artifacts of oversimplified assumptions or data gaps. It also provides a framework for iterative learning, whereby new information can be incorporated to refine understanding and reduce uncertainty over time (Deschaine, 2014, Kresic & Mikszewski, 2012).

In summary, the conceptual basis of subsurface contaminant transport underpins the effectiveness of spatially explicit risk modeling frameworks in data-limited remediation sites. Through an integrated understanding of hydrogeological processes, contaminant sources and pathways, and the structuring role of conceptual site models, it becomes possible to represent complex subsurface systems in a manner that supports risk-informed decision-making. This conceptual grounding allows spatial risk models to bridge the gap between limited empirical data and the practical need for defensible, transparent, and adaptive remediation strategies.

2.3. Data Constraints and Uncertainty in Remediation Environments

Data constraints and uncertainty are defining characteristics of many remediation environments, particularly in regions where historical contamination has accumulated over decades without systematic monitoring or documentation. In such settings, the ability to track subsurface contaminant migration is fundamentally shaped by the availability, quality, and spatial coverage of data. Understanding the nature of these constraints, and the uncertainty they introduce, is essential for developing spatially explicit risk modeling frameworks that remain credible and useful despite limited empirical inputs (Hipsey, et al., 2015, Scheidt, Li & Caers, 2018).

One of the most common data gaps in remediation sites relates to subsurface characterization. Detailed information on stratigraphy, hydraulic conductivity, porosity, and aquifer connectivity is often sparse or entirely absent. Borehole logs may be few in number, unevenly distributed, or derived from investigations conducted for purposes unrelated to contamination assessment, such as construction or water supply development. As a result, critical features such as low-permeability lenses, preferential flow paths, or vertical hydraulic gradients may go unrecognized. These omissions introduce structural uncertainty into contaminant transport assessments, as model representations of the subsurface may fail to capture pathways that strongly influence plume migration (Filippini, 2015, Mallants, et al., 2010).

Monitoring limitations further compound these challenges. Groundwater monitoring networks in resource-limited settings are frequently characterized by low spatial density and infrequent sampling intervals. Wells may be clustered near suspected source zones while down-gradient areas remain unsampled, obscuring plume extent and migration direction. Temporal data gaps are also common, with monitoring campaigns conducted sporadically due to funding constraints or logistical challenges (Binley, et al., 2015, Francisca, et al., 2012). This lack of temporal resolution limits the ability to distinguish between transient fluctuations and long-term trends in contaminant concentrations, increasing uncertainty in assessments of plume stability, attenuation, or expansion.

Chemical data limitations also play a significant role in shaping uncertainty. Analytical results may be restricted to a narrow set of contaminants, overlooking degradation products or co-contaminants that influence overall risk. Detection limits may be too high to capture low-level contamination that is nevertheless relevant for long-term exposure, particularly in drinking water contexts. In some cases, laboratory quality assurance information is incomplete, raising questions about data reliability. These chemical uncertainties complicate efforts to characterize contaminant behavior and assess exposure pathways accurately (Yaron, Dror & Berkowitz, 2012, Zeidan, 2017).

Historical data gaps represent another major source of uncertainty in remediation environments. Many contaminated sites lack reliable records of release timing, duration, and magnitude. Industrial practices may have changed repeatedly over time, with undocumented spills or disposal activities contributing to complex contamination patterns. Without a clear understanding of source history, it becomes difficult to determine whether observed contamination reflects ongoing releases, residual mass from past activities, or secondary sources such as contaminated soils acting as long-term reservoirs. This ambiguity directly affects predictions of future contaminant migration and the effectiveness of remediation measures (Kuppusamy, et al., 2016, Majone, et al., 2015). Figure 4 shows the experimental set-up for studying Back-Diffusion phenomena from low-permeability layers presented by Tatti, et al., 2016.

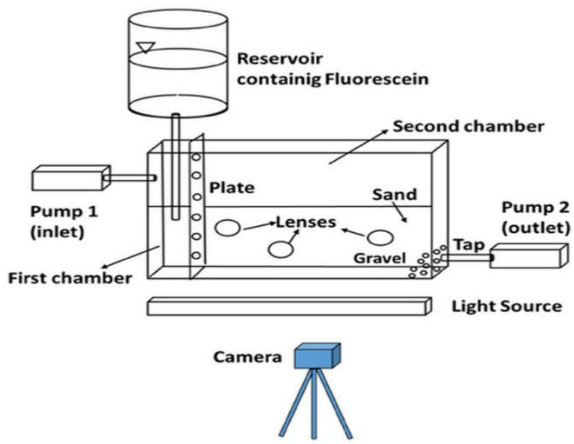

Figure 4: Experimental set-up for studying Back-Diffusion phenomena from low-permeability layers (Tatti, et al., 2016).

Hydrogeological boundary conditions are often poorly defined in data-limited settings, introducing additional uncertainty. Recharge rates, groundwater–surface water interactions, and regional flow directions may be inferred from limited regional studies rather than site-specific measurements. Seasonal variability in water levels and flow patterns may go undocumented, yet such variability can strongly influence contaminant transport and exposure risk. The inability to accurately characterize these boundary conditions undermines confidence in deterministic transport predictions and highlights the need for probabilistic or scenario-based approaches.

Uncertainty also arises from scale mismatches between available data and the processes of interest. Measurements collected at discrete points must be extrapolated across larger spatial domains to support decision-making, yet subsurface systems exhibit strong heterogeneity across multiple scales. This spatial extrapolation introduces interpolation uncertainty, particularly when data points are sparse or unevenly distributed. In data-limited remediation sites, the risk of misrepresenting contaminant plume geometry or risk gradients is significant if spatial variability is not adequately acknowledged (Essaid, Bekins & Cozzarelli, 2015, Kobus, Barczewski & Koschitzky, 2012).

Human and institutional factors further contribute to uncertainty in resource-limited remediation environments. Regulatory requirements may evolve over time, altering monitoring objectives and data collection priorities. Institutional memory may be lost due to staff turnover, leading to fragmented datasets and inconsistent documentation. Financial constraints can result in abbreviated investigations that prioritize compliance over comprehensive understanding, leaving critical uncertainties unresolved. These contextual factors shape not only the data available but also how uncertainty is perceived and managed in remediation decision-making (Gober & Kirkwood, 2010, Mark, et al., 2010).

Given these pervasive constraints, uncertainty in contaminant tracking is not merely a technical issue but a systemic feature of remediation practice in data-limited settings. Traditional modeling approaches that seek precise predictions based on extensive parameterization are often ill-suited to such environments, as they may convey a false sense of confidence or obscure underlying data limitations. Instead, acknowledging and explicitly addressing uncertainty becomes a central requirement for effective risk-based decision support.

Spatially explicit risk modeling frameworks respond to this challenge by reframing uncertainty as an integral component of analysis rather than a residual error to be minimized. By incorporating probabilistic representations, scenario analysis, and uncertainty propagation, these frameworks allow limited data to be used more transparently and defensibly. Rather than producing a single predicted plume boundary, spatial risk models generate ranges of plausible outcomes that reflect data gaps and monitoring limitations. This approach supports more informed prioritization of remediation actions, monitoring investments, and stakeholder engagement.

Importantly, recognizing data constraints also enables adaptive learning over time. By identifying areas where uncertainty is greatest and risk consequences are most significant, spatial risk models can guide targeted data acquisition that maximizes information gain. As new data become available, uncertainty can be reduced iteratively, improving model performance without requiring exhaustive site characterization from the outset. This adaptive approach is particularly valuable in resource-limited settings, where strategic allocation of limited funds is essential (Langat, Kumar & Koech, 2017, Nashwan, et al., 2018).

In conclusion, data gaps, monitoring limitations, and multiple sources of uncertainty are intrinsic to remediation environments characterized by limited resources and incomplete information. These constraints affect every aspect of subsurface contaminant tracking, from source characterization and pathway identification to risk assessment and remediation planning. A clear understanding of the nature and implications of these uncertainties is essential for developing spatially explicit risk modeling frameworks that are both realistic and useful. By explicitly incorporating uncertainty into analysis and decision-making, such frameworks provide a pragmatic pathway for improving contaminant tracking and risk management in data-limited remediation sites.

2.4. Framework Architecture and Methodological Design

The architecture and methodological design of a spatially explicit risk modeling framework for tracking subsurface contaminant migration in data-limited remediation sites is shaped by the need to balance scientific rigor with practical applicability under conditions of uncertainty and sparse data. Rather than attempting to replicate the complexity of fully coupled numerical groundwater flow and transport models, the framework is structured to integrate essential process understanding, geospatial analysis, and probabilistic reasoning into a coherent system that supports risk-informed decision-making. Its design prioritizes transparency, modularity, and adaptability, enabling practitioners to generate meaningful spatial risk insights while explicitly acknowledging data limitations (Hanson, et al., 2012, Wagesho, 2014).

At the foundation of the framework are geospatial inputs that provide the spatial context necessary for representing subsurface conditions and contaminant behavior. These inputs typically include site boundaries, topography, land-use patterns, surface hydrology, and the spatial distribution of known or suspected contaminant sources. Even in data-limited settings, such information is often available from satellite imagery, existing maps, or historical records. Subsurface data, such as borehole logs, groundwater level measurements, and limited chemical sampling results, are incorporated as point-based datasets that anchor the spatial analysis. Where direct measurements are scarce, proxy variables, including soil type classifications, depth to groundwater estimates, or proximity to potential receptors, are used to infer spatial variability relevant to contaminant transport and exposure risk (Leibowitz, et al., 2014, Ribeiro Neto, et al., 2014).

Geographic information systems serve as the primary platform for integrating and managing these diverse spatial datasets. The framework relies on GIS-based techniques to standardize data formats, align spatial resolutions, and interpolate point observations across the site domain. Interpolation methods are selected based on data density and quality, with simpler approaches such as inverse distance weighting or kriging employed where appropriate, and uncertainty-aware methods favored when data are sparse. Importantly, the framework treats interpolated surfaces not as definitive representations of reality but as probabilistic estimates that inform subsequent risk analysis (Nelitz, Boardley & Smith, 2013, Perra, et al., 2018).

A central feature of the methodological design is the incorporation of probabilistic components that explicitly account for uncertainty arising from data gaps, measurement error, and conceptual ambiguity. Rather than assigning single deterministic values to model parameters, the framework represents key variables, such as hydraulic gradients, contaminant concentrations, or attenuation rates, as probability distributions. These distributions are informed by available data, literature values, and expert judgment, reflecting both known variability and epistemic uncertainty. Bayesian inference techniques may be employed to update parameter distributions as new data become available, allowing the framework to evolve over time while maintaining internal consistency (Viviroli, et al., 2011, Watts, et al., 2015).

Scenario-based simulation forms another critical probabilistic element of the framework. Multiple plausible conceptual scenarios are defined to reflect alternative interpretations of subsurface conditions, source behavior, or transport mechanisms. For example, scenarios may differ in assumptions about aquifer connectivity, source persistence, or the effectiveness of natural attenuation processes. By propagating these scenarios through the spatial risk model, the framework generates a range of potential contaminant migration patterns and risk outcomes. This ensemble approach provides a more robust basis for decision-making than reliance on a single best-estimate model, particularly in data-limited environments (Edwards, et al., 2012, Green, 2016).

Simplified transport representations are employed to approximate contaminant migration processes without requiring intensive parameterization. These representations draw on conceptual understanding of advective flow, dispersion, and attenuation while avoiding the computational and data demands of fully numerical models. Transport is often modeled using spatial weighting functions that reflect likely migration directions and relative travel distances based on hydraulic gradients, topography, or inferred groundwater flow paths. Attenuation factors may be applied to account for dilution, sorption, or degradation processes, with uncertainty bounds reflecting limited site-specific information (Field, 2012, McMillan, et al., 2016).

The spatially explicit nature of the framework allows these simplified transport representations to be applied across heterogeneous site conditions. Risk is expressed as a spatially varying metric that integrates contaminant presence, migration potential, and exposure likelihood. Risk surfaces are generated by combining probabilistic contaminant distributions with spatial representations of receptors, such as water supply wells, surface water bodies, or populated areas. This integration enables visualization of risk gradients and identification of hotspots where intervention or further investigation may be warranted (Hubbard, et al., 2018, Singh, van Werkhoven & Wagener, 2014).

Methodologically, the framework is designed to be modular, allowing individual components to be refined or replaced as data availability and project objectives evolve. Geospatial layers can be updated with new measurements, probabilistic assumptions can be revised, and transport representations can be adjusted to reflect improved understanding. This modularity supports adaptive management, enabling the framework to remain relevant throughout different stages of site assessment and remediation.

Transparency is a key design principle underpinning the framework architecture. All assumptions, data sources, and modeling choices are documented and communicated clearly, ensuring that users understand the basis of model outputs and their associated uncertainties. This transparency enhances stakeholder trust and facilitates regulatory review, particularly in contexts where remediation decisions have significant social or environmental implications (Furniss, 2011, Handmer, et al., 2012).

The methodological design also emphasizes computational efficiency and accessibility. By avoiding overly complex numerical simulations, the framework can be implemented using commonly available GIS and statistical tools, making it accessible to practitioners working in resource-constrained settings. This accessibility supports broader adoption and encourages consistent application across multiple sites, promoting comparability and knowledge transfer.

In practice, the framework functions as a decision-support tool rather than a predictive oracle. Its outputs are intended to inform prioritization, guide targeted data collection, and support evaluation of remediation strategies under uncertainty. By integrating geospatial inputs, probabilistic reasoning, and simplified transport representations, the framework provides a balanced approach that respects the limitations of available data while delivering actionable insights (Kato, 2010, Meerow & Newell, 2017).

In summary, the architecture and methodological design of the spatially explicit risk modeling framework reflect a deliberate response to the challenges of tracking subsurface contaminant migration in data-limited remediation sites. Through the integration of geospatial data, probabilistic components, and simplified transport models, the framework offers a practical, transparent, and adaptive means of supporting risk-informed decision-making. It bridges the gap between qualitative conceptual understanding and data-intensive numerical modeling, enabling more resilient and effective remediation planning in environments where uncertainty is the norm rather than the exception.

2.5. Spatial Analysis and Risk Quantification Techniques

Spatial analysis and risk quantification techniques are central to the effectiveness of a spatially explicit risk modeling framework for tracking subsurface contaminant migration in data-limited remediation sites. In environments where empirical observations are sparse and uncertainty is high, these techniques provide the analytical means to translate limited point-based information into spatially continuous representations of risk that can support informed decision-making. The emphasis is not on achieving exact predictions, but on developing defensible, transparent, and interpretable spatial outputs that reflect both available evidence and associated uncertainty (Jayasooriya, 2016, Sayles, 2017).

Interpolation methods form the initial step in transforming discrete measurements into spatially continuous datasets. Groundwater contaminant concentrations, hydraulic heads, or soil properties are typically available only at a limited number of sampling locations, yet understanding their spatial distribution is critical for assessing migration pathways and exposure risks. Simple deterministic interpolation techniques such as inverse distance weighting are often employed in data-limited settings due to their minimal data requirements and ease of interpretation. These methods assign greater influence to nearby observations while progressively reducing the weight of distant points, providing a straightforward means of estimating values in unsampled areas. While such approaches may not capture complex spatial patterns, they offer a pragmatic starting point when data density precludes more sophisticated analysis (Ferdinand & Yu, 2016, Koop & van Leeuwen, 2017).

Geostatistical methods, particularly kriging, provide an alternative interpolation framework that explicitly incorporates spatial autocorrelation and estimation uncertainty. Even when datasets are sparse, exploratory variogram analysis can offer insights into spatial structure at a coarse level, allowing kriging to generate both estimated surfaces and associated uncertainty measures. In data-limited remediation sites, kriging is often applied in a simplified or constrained form, with variogram models informed by regional analogs or literature values rather than extensive site-specific calibration (Boriana, 2017, Hou & Al-Tabbaa, 2014). The resulting uncertainty maps are particularly valuable for risk modeling, as they highlight areas where predictions are least reliable and where additional data collection may yield the greatest benefit.

Interpolation uncertainty is a critical consideration in subsurface contaminant tracking, as it directly influences subsequent risk estimates. Rather than treating interpolated surfaces as fixed inputs, spatially explicit risk frameworks often propagate interpolation uncertainty through later stages of analysis. This propagation ensures that risk estimates reflect not only observed contaminant levels but also the confidence associated with spatial predictions. Such an approach is especially important in data-limited contexts, where overconfidence in interpolated results can lead to misguided remediation decisions (Cheng, et al., 2011, Herat & Agamuthu, 2012).

Bayesian and scenario-based risk estimation techniques provide a structured means of integrating uncertainty into spatial analysis. Bayesian methods are particularly well suited to data-limited environments because they allow prior knowledge, such as regional hydrogeological characteristics or contaminant behavior reported in the literature, to be combined with limited site-specific data. Probability distributions are assigned to key parameters, and Bayesian updating is used to refine these distributions as new information becomes available. This probabilistic framework enables explicit quantification of uncertainty and supports iterative learning, aligning well with adaptive remediation strategies (Mitchell, 2012, Sweeney & Kabouris, 2017).

Scenario-based approaches complement Bayesian methods by exploring alternative conceptual interpretations of site conditions and contaminant behavior. In the absence of sufficient data to discriminate conclusively between competing hypotheses, multiple plausible scenarios are defined and evaluated in parallel. These scenarios may differ in assumptions about contaminant source strength, transport pathways, attenuation mechanisms, or boundary conditions. By generating spatial risk estimates for each scenario, the framework captures the range of potential outcomes and avoids reliance on a single, potentially misleading representation of reality. Decision-makers can then assess risk robustness across scenarios and prioritize actions that remain effective under multiple plausible futures.

Risk quantification within the framework typically involves integrating contaminant presence or concentration estimates with information on exposure pathways and receptor vulnerability. In spatial terms, this integration is achieved by combining interpolated contaminant surfaces with geospatial layers representing land use, water supply infrastructure, ecological receptors, or population distribution. Risk metrics may be expressed as probability of exceedance of regulatory thresholds, relative risk indices, or composite scores that reflect multiple risk dimensions. The choice of metric is guided by decision-making needs, regulatory context, and data availability, with simplicity and transparency favored in data-limited settings (Cappuyns & Kessen, 2014, Williamson, et al., 2011).

The generation of spatial risk surfaces represents the culmination of the spatial analysis and risk quantification process. These surfaces visualize how risk varies across the site, highlighting gradients, hotspots, and areas of elevated uncertainty. Spatial risk maps serve as powerful decision-support tools, enabling stakeholders to quickly identify priority areas for further investigation, remediation, or monitoring. In data-limited remediation sites, where resources must be allocated strategically, such visualizations support efficient and targeted interventions.

Importantly, spatial risk surfaces are not static products but dynamic representations that evolve as new data are incorporated. The framework supports iterative updating of risk maps, allowing changes in risk distribution to be tracked over time. This temporal dimension enhances the utility of spatial risk modeling for monitoring remediation progress and evaluating the effectiveness of management actions. In addition, uncertainty overlays can be generated alongside risk surfaces, providing decision-makers with explicit information on confidence levels and data limitations (Hardie & McKinley, 2014, Williamson, 2011).

The communicative value of spatial risk surfaces is a key advantage of spatially explicit risk modeling frameworks. By translating complex analytical outputs into intuitive visual formats, these surfaces facilitate dialogue among technical experts, regulators, and affected communities. Clear visualization of both risk and uncertainty helps manage expectations, supports transparency, and builds trust in decision-making processes, particularly in contexts where data limitations may otherwise undermine confidence (An, et al., 2016, Mgbeahuruike, 2018).

Despite their utility, spatial analysis and risk quantification techniques must be applied with caution in data-limited settings. Overinterpretation of interpolated surfaces or probabilistic outputs can obscure underlying uncertainties if not accompanied by clear documentation and explanation. The framework addresses this challenge by embedding uncertainty communication into the modeling process, ensuring that spatial risk outputs are presented as decision-support tools rather than definitive predictions.

In summary, spatial analysis and risk quantification techniques are integral to enabling subsurface contaminant tracking in data-limited remediation sites. Through the judicious application of interpolation methods, Bayesian and scenario-based risk estimation, and the generation of spatial risk surfaces, the framework transforms limited and uncertain data into actionable insights. By explicitly representing uncertainty and supporting adaptive decision-making, these techniques enhance the robustness, transparency, and practical relevance of spatially explicit risk modeling in challenging remediation environments.

2.6. Model Implementation and Adaptive Application

Model implementation and adaptive application are critical to translating a spatially explicit risk modeling framework from a conceptual and methodological construct into a practical decision-support tool for tracking subsurface contaminant migration in data-limited remediation sites. In such environments, successful implementation depends not only on technical soundness but also on flexibility, transparency, and the capacity to evolve as new information becomes available. The framework is therefore designed to support stepwise deployment, iterative data integration, and continuous refinement of risk estimates through adaptive management principles (Lemming, 2010, Wang, et al., 2017).

The initial implementation of the framework begins with the assembly and evaluation of all available data relevant to the site. This includes geospatial datasets such as site boundaries, topography, land use, surface drainage networks, and infrastructure, as well as subsurface information derived from borehole logs, groundwater level measurements, and chemical sampling results. Given the data-limited nature of many remediation sites, this step also involves identifying proxy datasets and secondary information sources that can inform spatial patterns, such as regional hydrogeological maps or historical land-use records (Ahmed, 2017, Karpatne, et al., 2018). Data quality assessment is an essential component of this stage, as it establishes confidence levels, identifies inconsistencies, and informs subsequent uncertainty treatment.

Once data are compiled, the framework is deployed within a geospatial analysis environment that supports spatial interpolation, probabilistic modeling, and visualization. The spatial domain is discretized into an appropriate grid or set of spatial units that balance resolution with data availability. At this stage, initial interpolated surfaces of key variables, such as contaminant concentrations or groundwater elevations, are generated using methods suitable for sparse datasets. These surfaces provide a preliminary spatial representation of subsurface conditions, serving as a baseline for risk assessment rather than a definitive depiction of contaminant distribution (Liakos, et al., 2018, Singh, Gupta & Mohan, 2014).

Risk estimation is then conducted by integrating spatial contaminant representations with information on potential receptors and exposure pathways. Probabilistic assumptions are applied to key parameters to reflect uncertainty arising from data gaps and measurement limitations. Initial risk surfaces are generated to identify areas of elevated concern and to highlight zones where uncertainty is greatest. Importantly, these outputs are treated as provisional and are accompanied by clear documentation of assumptions, data sources, and limitations to support transparent interpretation.

Adaptive application of the framework is enabled through its iterative structure, which allows new data to be incorporated as they become available. In data-limited remediation sites, data acquisition often occurs incrementally, driven by regulatory requirements, budget cycles, or targeted investigations. The framework accommodates this reality by allowing new monitoring results, borehole information, or laboratory analyses to be integrated without requiring a complete model rebuild. Instead, new data are assimilated into existing geospatial layers and probabilistic distributions, updating interpolated surfaces and refining risk estimates accordingly (Naghibi, Pourghasemi & Dixon, 2016, Rodriguez-Galiano, et al., 2014).

Bayesian updating techniques play a key role in this iterative integration process. As new observations are introduced, prior parameter distributions are revised to reflect increased knowledge, reducing uncertainty where data support stronger inference. This process ensures that risk estimates evolve in a statistically coherent manner, avoiding abrupt or unjustified changes in model outputs. Where Bayesian methods are not feasible, scenario refinement offers an alternative means of adaptive updating, allowing certain scenarios to be deprioritized or revised as evidence accumulates.

Adaptive management principles guide how refined risk estimates are used to inform remediation decision-making. Rather than pursuing a fixed remediation plan based on initial assessments, the framework supports a cyclical process of assessment, action, monitoring, and reassessment. Early risk maps may be used to prioritize further investigation in high-uncertainty or high-risk areas, ensuring that limited resources are directed toward activities with the greatest potential impact. Subsequent data collection efforts are then informed by these priorities, creating a feedback loop that progressively improves site understanding (Park, et al., 2016, Ransom, et al., 2017).

Model refinement also involves periodic evaluation of conceptual assumptions underpinning the framework. As new data are integrated, discrepancies between predicted and observed conditions may emerge, prompting reassessment of transport pathways, source behavior, or attenuation mechanisms. The framework's modular design allows these conceptual elements to be revised without destabilizing the entire modeling structure. This flexibility is particularly important in complex subsurface environments, where initial assumptions may require adjustment as understanding improves (Barzegar, et al., 2018, Karandish, Darzi-Naftchali & Asgari, 2017).

Effective implementation also requires careful attention to stakeholder engagement and communication. Spatial risk outputs are shared with regulators, site managers, and affected communities to support informed dialogue and collaborative decision-making. By presenting risk estimates alongside uncertainty information, the framework helps manage expectations and fosters trust, even when data limitations constrain predictive certainty. Feedback from stakeholders can, in turn, inform model refinement by highlighting practical considerations or knowledge not captured in formal datasets.

Operationally, adaptive application of the framework supports phased remediation strategies that can be adjusted in response to evolving risk profiles. For example, interim containment measures may be implemented in high-risk zones while further data are collected to inform long-term remediation planning. As risk surfaces are updated, remediation priorities can be re-evaluated, ensuring that actions remain aligned with current understanding rather than outdated assumptions.

Documentation and version control are essential components of adaptive model implementation. Each iteration of the framework, including data updates, parameter revisions, and changes in assumptions, is recorded to maintain traceability and accountability. This documentation supports regulatory review, facilitates knowledge transfer among project teams, and enables retrospective evaluation of decision-making processes (Burritt, Schaltegger & Zvezdov, 2011, Gibassier & Schaltegger, 2015).

In data-limited remediation sites, adaptive application of spatially explicit risk modeling frameworks also contributes to capacity building and institutional learning. By demonstrating how limited data can be used effectively through structured analysis and iterative refinement, the framework encourages more systematic and transparent remediation practices. Over time, this approach can lead to improved data collection strategies, better resource allocation, and enhanced confidence in risk-informed decision-making.

In summary, model implementation and adaptive application are central to the practical success of spatially explicit risk modeling frameworks in data-limited remediation sites. Through stepwise deployment, iterative data integration, and continuous refinement of risk estimates, the framework supports adaptive management that responds to uncertainty rather than being constrained by it. By embedding flexibility, transparency, and learning into the modeling process, the framework enables more effective tracking of subsurface contaminant migration and more resilient remediation outcomes in challenging, resource-constrained environments.

2.7. Implications for Remediation Planning and Policy

The application of a spatially explicit risk modeling framework for tracking subsurface contaminant migration in data-limited remediation sites carries significant implications for remediation planning and environmental policy. In contexts where uncertainty, limited monitoring infrastructure, and constrained resources dominate decision-making, such frameworks offer a structured means of aligning technical analysis with practical and regulatory needs. By explicitly integrating spatial variability and uncertainty into risk assessment, the framework reshapes how remediation priorities are defined, strategies are selected, and policies are operationalized (Ascui & Lovell, 2012, Steininger, et al., 2016).

One of the most immediate implications of the framework is its capacity to support strategic sampling prioritization. In data-limited environments, indiscriminate expansion of monitoring networks is often impractical due to financial, logistical, or institutional constraints. Spatially explicit risk modeling enables decision-makers to identify zones where uncertainty and potential risk intersect, allowing limited sampling efforts to be directed toward locations that are most informative for reducing uncertainty or confirming risk hypotheses. Rather than treating all unsampled areas as equally important, the framework highlights spatial gradients and hotspots that warrant focused investigation (Ascui, 2014, Hartmann, Perego & Young, 2013). This targeted approach enhances the efficiency of data collection, accelerates learning about site conditions, and improves the overall quality of subsequent risk assessments.

The framework also has important implications for remedial strategy selection. Traditional remediation planning in data-scarce settings often relies on conservative assumptions that may lead to overly broad or costly interventions. Spatial risk modeling introduces a more nuanced understanding of contaminant distribution and migration potential, enabling remediation strategies to be tailored to site-specific risk patterns. By distinguishing areas of high, moderate, and low risk, the framework supports the deployment of differentiated remediation measures, such as active treatment in critical zones, containment or monitoring in transitional areas, and natural attenuation where risks are demonstrably low (Maas, Schaltegger & Crutzen, 2016, Tang & Luo, 2014). This risk-informed stratification improves the cost-effectiveness of remediation while maintaining protection of human health and the environment.

Uncertainty-aware risk estimates further enhance remedial decision-making by encouraging adaptive strategies rather than rigid, one-time interventions. Policymakers and practitioners can use spatial risk outputs to evaluate the robustness of proposed remediation actions under different plausible scenarios. Strategies that perform acceptably across a range of uncertainty conditions can be favored over those that are highly sensitive to specific assumptions. This resilience-oriented approach aligns remediation planning with adaptive management principles, allowing strategies to be refined as new information becomes available (Bowen & Wittneben, 2011, Schaltegger & Csutora, 2012).

Stakeholder communication is another area where the implications of the framework are particularly significant. Remediation decisions often involve diverse stakeholders, including regulators, site owners, affected communities, and technical experts, each with different perspectives and information needs. Spatial risk maps generated by the framework provide an intuitive and accessible means of communicating complex technical information. By visualizing risk gradients and uncertainty explicitly, these maps facilitate shared understanding and constructive dialogue. Stakeholders can more readily grasp why certain areas are prioritized for action or monitoring, reducing misunderstandings and building trust in the decision-making process (Hoek, Beelen & Brunekreef, 2011, Levy, 2013).

In data-limited contexts, transparency about uncertainty is especially important for maintaining stakeholder confidence. The framework's explicit treatment of uncertainty helps manage expectations by clarifying what is known, what is uncertain, and how decisions are being made despite these limitations. This openness can mitigate conflict and support more inclusive decision-making, particularly in communities that may be skeptical of remediation efforts due to past experiences or perceived inequities.

From a regulatory perspective, the spatially explicit risk modeling framework offers a valuable tool for supporting compliance and evidence-based policy implementation. Regulatory agencies often require demonstration that remediation decisions are grounded in sound scientific reasoning, even when data are limited. By providing a documented and transparent analytical process that integrates available data, expert judgment, and uncertainty analysis, the framework strengthens the defensibility of remediation plans (Derycke, et al., 2018, Kulawiak & Lubniewski, 2014). Regulators can use spatial risk outputs to evaluate whether proposed actions are proportionate to risk and consistent with regulatory objectives.

The framework also supports risk-based regulatory approaches that prioritize outcomes rather than prescriptive methods. In many jurisdictions, there is growing emphasis on flexible, performance-oriented regulation that allows site managers to select remediation strategies appropriate to local conditions. Spatially explicit risk modeling aligns with this trend by enabling regulators to assess whether risk reduction goals are being met across the site, rather than focusing solely on compliance at individual monitoring points. This shift can be particularly beneficial in data-limited settings, where rigid compliance requirements may be difficult to satisfy or may divert resources away from more impactful actions.

Policy implications extend beyond individual sites to broader remediation programs and land management strategies. Aggregated insights from spatial risk models can inform regional prioritization of remediation efforts, helping policymakers allocate limited public resources more effectively. By identifying patterns of risk across multiple sites, the framework can support strategic planning at the watershed, municipal, or regional scale. This broader perspective is essential for addressing cumulative impacts and advancing environmental justice in areas disproportionately affected by contamination (Roghani, 2018, Wang, Unger & Parker, 2014).

The framework also encourages integration between remediation planning and land-use policy. Spatial risk information can inform decisions about redevelopment, zoning, or infrastructure investment by clarifying where contamination risks may constrain future land use. In data-limited contexts, such foresight is critical for avoiding unintended exposure pathways or costly remediation retrofits. Policymakers can use spatial risk outputs to guide sustainable land-use planning that accounts for subsurface contamination risks while supporting economic and social development.

Despite these benefits, the policy implications of spatially explicit risk modeling also include the need for capacity building and institutional support. Effective use of the framework requires technical expertise in geospatial analysis, probabilistic modeling, and risk communication. Policymakers must therefore consider investments in training, data infrastructure, and cross-sector collaboration to ensure that the framework can be implemented consistently and effectively. Without such support, there is a risk that sophisticated tools may be underutilized or misinterpreted (McAlary, Provoost & Dawson, 2010, Provoost, et al., 2013).

In conclusion, the spatially explicit risk modeling framework has far-reaching implications for remediation planning and policy in data-limited contexts. By supporting targeted sampling, risk-informed remedial strategy selection, transparent stakeholder communication, and defensible regulatory compliance, the framework enhances the effectiveness and legitimacy of remediation decision-making. Its emphasis on spatial variability and uncertainty aligns remediation practice with adaptive management and evidence-based policy, offering a pragmatic pathway for managing subsurface contamination under constrained conditions. Through thoughtful integration into planning and regulatory processes, the framework can contribute to more efficient, equitable, and sustainable remediation outcomes (Andres, et al., 2018, Turczynowicz, Pisaniello & Williamson, 2012).

2.8. Conclusion

This study has presented a spatially explicit risk modeling framework as a pragmatic and robust approach for tracking subsurface contaminant migration in remediation environments characterized by limited data availability. The framework's primary contribution lies in its integration of geospatial analysis, probabilistic reasoning, and simplified contaminant transport representations to support risk-informed decision-making under uncertainty. By shifting emphasis from precise plume prediction to spatially resolved risk estimation, the framework bridges the gap between qualitative conceptual site understanding and data-intensive numerical models, offering a defensible alternative for early-stage assessment and adaptive remediation planning in resource-constrained settings.

A key strength of the framework is its ability to explicitly incorporate uncertainty arising from data gaps, sparse monitoring networks, and incomplete subsurface characterization. Through the use of probabilistic components, scenario-based analysis, and uncertainty-aware spatial interpolation, the framework provides transparent risk estimates that reflect both available evidence and inherent limitations. Its spatially explicit structure enables visualization of risk gradients and hotspots, supporting targeted sampling, efficient allocation of remediation resources, and improved communication among regulators, practitioners, and affected communities. The modular and adaptive design further enhances its practical value, allowing iterative refinement as new data become available without requiring complete model reconstruction.

Despite these strengths, the framework has inherent limitations that must be acknowledged. Simplified transport representations, while necessary in data-limited contexts, cannot capture the full complexity of subsurface processes in highly heterogeneous or fractured systems. The reliability of spatial risk outputs remains dependent on the quality of underlying data and the validity of conceptual assumptions, meaning that results should be interpreted as decision-support tools rather than definitive predictions. In addition, effective implementation requires technical capacity in geospatial and probabilistic analysis, which may be limited in some institutional or regional contexts. Without appropriate training and governance structures, there is a risk of misinterpretation or overreliance on model outputs.

Future directions for advancing spatial risk modeling in subsurface contamination management include the integration of emerging data sources, such as remote sensing products, low-cost sensor networks, and crowdsourced environmental data, to enhance spatial coverage in data-scarce environments. Advances in machine learning and hybrid modeling approaches also offer opportunities to improve pattern recognition and uncertainty handling while maintaining interpretability. Strengthening links between spatial risk modeling and regulatory frameworks will further support risk-based remediation policies that are flexible, transparent, and outcome-oriented. Ultimately, continued development and application of spatially explicit risk modeling frameworks can contribute to more resilient, equitable, and sustainable management of subsurface contamination, particularly in settings where uncertainty and resource constraints are unavoidable realities.

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