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Geospatial Decision-Support System for Prioritizing Environmental Interventions in Complex Industrial Legacy Sites

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Abstract
Industrial legacy sites present persistent environmental and public health challenges due to heterogeneous contamination, fragmented historical records, and competing remediation priorities. Decision-makers often face difficulties in allocating limited resources effectively across complex spatial contexts characterized by uncertainty, multiple stakeholders, and interacting risk pathways. This study proposes a Geospatial Decision-Support System (GDSS) designed to prioritize environmental interventions in complex industrial legacy sites by integrating spatial analytics, multi-criteria decision analysis, and risk-based assessment within a unified computational framework. The proposed system synthesizes geospatial datasets including land use history, contaminant distribution, hydrogeological conditions, population vulnerability, ecological receptors, and infrastructure constraints to generate transparent, evidence-based prioritization outputs. A modular architecture is adopted, enabling flexible data ingestion, scenario testing, and iterative updating as new information becomes available. Spatial weighting and normalization techniques are combined with expert-informed criteria scoring to capture both quantitative indicators and contextual knowledge that are often excluded from conventional remediation planning tools. The GDSS incorporates uncertainty handling through sensitivity analysis and probabilistic overlays, allowing users to examine how data gaps and assumption variability influence intervention rankings. Visualization dashboards translate complex analytical results into intuitive maps and decision matrices that support stakeholder communication and regulatory engagement. The framework is particularly suited to data-limited environments where monitoring coverage is uneven and historical contamination patterns are poorly constrained. By explicitly linking spatial risk profiles to intervention feasibility and potential impact, the system supports strategic sequencing of remediation actions, optimization of monitoring investments, and alignment with sustainability and land-reuse objectives. A conceptual application demonstrates how the GDSS can differentiate high-priority zones requiring immediate intervention from areas suitable for long-term management or redevelopment planning. The study contributes a scalable and adaptable decision-support approach that enhances transparency, consistency, and accountability in environmental management of industrial legacy sites. Overall, the proposed GDSS advances geospatially informed environmental governance by enabling more rational, defensible, and impact-oriented prioritization of interventions under conditions of complexity and uncertainty. Its design supports integration with policy frameworks, community engagement processes, and adaptive management strategies, ensuring that remediation decisions remain responsive to evolving environmental conditions, regulatory expectations, and socio-economic development goals over extended project lifecycles. Globally applicable.

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1. Introduction

Industrial legacy sites represent one of the most persistent and complex environmental management challenges worldwide. These sites, shaped by decades of industrial activity such as mining, manufacturing, chemical processing, and waste disposal, are often characterized by diffuse contamination, overlapping pollution sources, and long-term ecological and human health risks. The environmental burden associated with such sites is compounded by fragmented historical records, evolving land-use patterns, and regulatory pressures to balance remediation with socio-economic redevelopment. Decision-makers are frequently confronted with competing intervention needs across spatially heterogeneous landscapes, where limited financial and technical resources must be allocated in a manner that maximizes risk reduction and long-term sustainability (Afolabi, *et al*., 2020, Bankole, Nwokediegwu & Okiye, 2020).

Traditional approaches to environmental intervention planning at industrial legacy sites have often relied on site-by-site assessments or isolated risk metrics, which inadequately capture spatial interactions and cumulative impacts. These methods can struggle to address interconnected contamination pathways, variable exposure scenarios, and differing levels of community vulnerability within and across sites. As a result, intervention prioritization may become reactive, opaque, or misaligned with broader environmental and development objectives. The increasing complexity of legacy site management therefore demands more integrative, transparent, and defensible decision-support approaches that can synthesize diverse data sources and support strategic planning under uncertainty (Fasasi, *et al*., 2020, Giwah, *et al*., 2020).

Geospatially driven decision-support systems offer a compelling response to these challenges by embedding spatial intelligence at the core of environmental prioritization. Advances in geographic information systems, spatial analytics, and decision science now enable the integration of environmental, hydrogeological, socio-economic, and infrastructural data within a single analytical environment. By explicitly representing spatial relationships and variability, geospatial decision-support systems facilitate more nuanced understanding of risk distribution, intervention feasibility, and potential downstream effects. These systems also enhance communication among regulators, technical experts, and stakeholders through visual outputs that translate complex analyses into accessible decision-relevant insights (Fasasi & Ekechi, 2020, Lawoyin, Nwokediegwu & Gbabo, 2020).

The objective of this study is to develop and articulate a Geospatial Decision-Support System for prioritizing environmental interventions in complex industrial legacy sites. The proposed framework is designed to support evidence-based ranking of intervention zones by integrating spatial risk indicators, multi-criteria decision analysis, and uncertainty considerations within a coherent structure. The scope of the study encompasses conceptual system design, data integration logic, and decision-support functionality applicable to data-rich and data-limited contexts alike. By advancing a geospatially informed approach to intervention prioritization, this work seeks to contribute to more effective, transparent, and adaptive environmental governance in industrial legacy landscapes (Fasasi, *et al*., 2020, Lawoyin, Nwokediegwu & Gbabo, 2020).

2. Methodology

The methodology adopted a design-science and evidence-synthesis approach to develop and demonstrate a Geospatial Decision-Support System (GDSS) for prioritizing environmental interventions in complex industrial legacy sites. The process began with problem scoping and boundary definition, where the legacy site extent, decision objectives, regulatory constraints, and priority receptors (human and ecological) were specified to frame the decision context. To ensure that system criteria were defensible and aligned with established scientific practice, an evidence synthesis procedure was applied, drawing on systematic review logic used in process-technology selection studies to build a criteria and indicators library that is auditable and reusable (Afolabi *et al*., 2020a; Afolabi *et al*., 2020b). This library was complemented with stakeholder and expert elicitation to reflect local context, consistent with participatory planning support principles for complex environments (Van Cauwenbergh *et al*., 2018).

A multi-source data acquisition strategy was then implemented to populate the GDSS. Geospatial inputs included base maps, land-use/land-cover, digital elevation models, drainage networks, infrastructure, and parcel boundaries. Environmental inputs included soil, groundwater, surface-water and sediment quality results, monitoring time series where available, and pathway-relevant parameters; remote sensing and in-situ monitoring concepts were incorporated to support scalable observation in data-limited contexts (Andres *et al*., 2018). Socio-economic inputs included population density, sensitive receptors (schools and healthcare), vulnerability proxies, and redevelopment constraints, reflecting the need to integrate human exposure and equity considerations with technical risk. Data governance and access control requirements were documented to maintain integrity and reduce misuse of sensitive location information, consistent with metadata-driven control principles in high-risk analytics contexts (Olatunde-Thorpe *et al*., 2020).

All datasets underwent preprocessing and harmonization. Quality assurance checks were applied to detect missing values, inconsistent units, duplicates, and outliers. Spatial layers were transformed into a common coordinate reference system, resampled to an agreed analysis resolution, and aligned to a shared spatial unit (grid cells, parcels, or hybrid management zones). Variables were standardized and normalized to enable comparability across different units and magnitudes, preparing inputs for multi-criteria evaluation. Where monitoring data were sparse, spatial estimation was performed using interpolation and/or machine-learning risk mapping concepts that have proven effective for groundwater contamination risk and nitrate prediction, including ensemble approaches where appropriate (Barzegar *et al*., 2018; Ransom *et al*., 2017). The modeling workflow supported both intrinsic vulnerability representation and site-specific stressors, with geospatial overlays used to integrate contamination sources, transport corridors, exposure opportunities, and receptor distributions.

Indicator construction followed a risk-chain structure. Contamination indicators summarized concentration exceedance, mixture burden, and persistence/mobility potential. Exposure indicators represented pathway connectivity and receptor proximity, including land-use-informed exposure likelihood and vapor/indoor-air sensitivity proxies where applicable to legacy urban settings (Turczynowicz *et al*., 2012; Levy, 2013). Vulnerability indicators captured population susceptibility and sensitivity of critical facilities, informed by environmental assessment considerations around schools near former industrial facilities (Derycke *et al*., 2018). Feasibility indicators represented access constraints, infrastructure conflicts, land-use restrictions, and implementation practicality.

Prioritization used GIS-based Multi-Criteria Decision Analysis (MCDA) as the core decision algorithm, consistent with established GIS–MCDA approaches for spatial site decision problems (Rikalovic *et al*., 2014) and remediation technology/strategy evaluation using fuzzy MCDA when ambiguity and linguistic judgments were unavoidable (Wang *et al*., 2017). A hybrid decision engine was implemented: (i) weighted linear combination for transparent baseline ranking, (ii) Analytic Hierarchy Process (AHP) for structured weight elicitation where stakeholders could provide pairwise preferences, and (iii) fuzzy membership functions to convert qualitative judgments (e.g., "high feasibility," "moderate vulnerability") into numeric comparators where crisp thresholds would be misleading. The system produced a composite priority index per spatial unit and generated decision matrices showing criterion contributions to each rank, supporting explainability and auditability.

Uncertainty handling was embedded throughout. Data gaps were represented using confidence scores and missingness flags, while uncertain inputs were propagated using scenario analysis and Monte Carlo sampling of key parameters and weights. Sensitivity testing included one-at-a-time and global perturbation of criterion weights, alternative normalization schemes, and alternative spatial estimation models to evaluate ranking stability and identify "high-confidence" priority zones versus "data-sensitive" zones requiring more sampling. This is consistent with multi-model thinking in environmental prediction and the need to test robustness under competing assumptions (Perra *et al*., 2018; Karpatne *et al*., 2018).

Finally, the GDSS outputs were operationalized through map products, dashboards, and decision matrices that support regulatory review and participatory communication. Validation proceeded through triangulation: comparison with known hotspots, targeted field verification, and expert/regulator review, followed by iterative refinement of criteria weights and data inputs. The workflow was designed for integration into remediation planning, sequencing, and adaptive monitoring cycles, enabling periodic updates as new in-situ or remote sensing observations become available (Andres *et al*., 2018) and ensuring the GDSS remains a living tool rather than a one-off assessment.

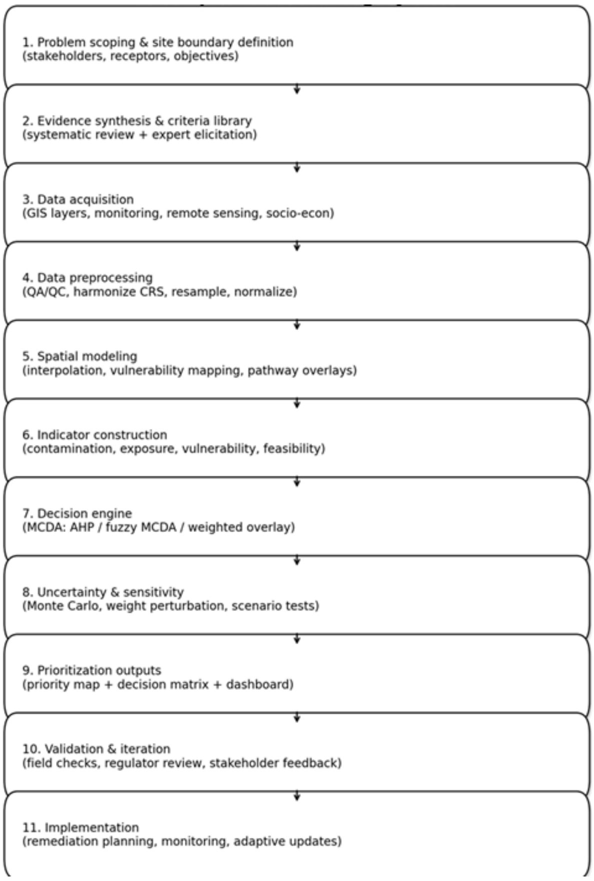

Fig 1: Flowchart of the study methodology

3. Context and Complexity of Industrial Legacy Sites

Industrial legacy sites are the cumulative outcome of prolonged industrial activities whose environmental footprints persist long after operations have ceased or transformed. These sites are typically associated with sectors such as mining, petrochemicals, metallurgy, manufacturing, power generation, waste disposal, and heavy engineering, all of which historically operated under regulatory regimes that placed limited emphasis on environmental protection. As a result, legacy contamination is often deeply embedded within soil, groundwater, surface water, sediments, and built infrastructure, creating complex risk profiles that challenge conventional environmental management approaches. Understanding the context and complexity of these sites is fundamental to the design and application of a geospatial decision-support system capable of prioritizing environmental interventions in a defensible and effective manner (Ike, *et al*., 2018).

The types and sources of legacy industrial contamination are highly diverse and site-specific, reflecting the nature of past industrial processes, materials handled, and waste management practices. Common contaminants include heavy metals such as lead, mercury, cadmium, and arsenic originating from smelting, mining, and battery manufacturing; hydrocarbons and polycyclic aromatic hydrocarbons associated with petroleum refining, fuel storage, and gasworks; chlorinated solvents from degreasing and chemical processing; persistent organic pollutants such as polychlorinated biphenyls and dioxins; and a wide range of emerging contaminants linked to historical industrial formulations. These substances may exist in multiple environmental media simultaneously, interacting through complex transport pathways such as leaching, volatilization, erosion, and bioaccumulation (Nwokediegwu, Bankole & Okiye, 2019, Oshoba, Hammed & Odejobi, 2019). In many cases, contamination sources overlap spatially and temporally, making it difficult to isolate individual contributors or attribute observed impacts to specific historical activities. This multiplicity of contaminant types and sources complicates risk assessment and demands an integrative analytical perspective that can account for cumulative and synergistic effects.

Spatial heterogeneity is a defining characteristic of industrial legacy sites and represents one of the greatest challenges for environmental intervention planning. Contaminant concentrations often vary significantly over short distances due to localized disposal practices, preferential flow paths, variable soil properties, and structural remnants such as buried foundations, pipelines, and waste pits. Vertical heterogeneity is equally important, with contamination distributed unevenly across soil horizons and aquifer layers. This spatial complexity is frequently exacerbated by incomplete or inconsistent historical data, as records of industrial operations, waste disposal locations, and chemical usage may be missing, inaccurate, or inaccessible. Many legacy sites predate modern environmental monitoring requirements, resulting in significant uncertainty regarding the extent, magnitude, and evolution of contamination (Fasasi & Ekechi, 2020, Giwah, *et al*., 2020). Even where monitoring data exist, they are often sparse, unevenly distributed, or collected using outdated methodologies that limit comparability. Such uncertainty undermines confidence in traditional point-based assessments and highlights the need for spatially explicit tools capable of synthesizing fragmented information while explicitly representing data gaps and variability.

The uncertainty associated with historical data is not solely technical but also epistemic, arising from incomplete knowledge about past industrial behaviors and environmental processes. Changes in site ownership, corporate restructuring, and the passage of time further complicate efforts to reconstruct contamination histories. Natural attenuation processes, remedial actions undertaken without comprehensive documentation, and land-use changes can obscure original contamination patterns, making it difficult to distinguish legacy impacts from more recent disturbances. In this context, decision-makers are often required to act under conditions of imperfect information, balancing precautionary principles against economic and practical considerations (Olatunde-Thorpe, *et al*., 2020, Oshoba, *et al*., 2020). A geospatial decision-support system must therefore be capable of incorporating uncertainty as an explicit dimension of analysis rather than treating it as an external limitation. Figure 2 shows the interaction between the GIS, Planning Process and Decision Support System presented by Sultani, Soliman & Al-Hagla, 2009.

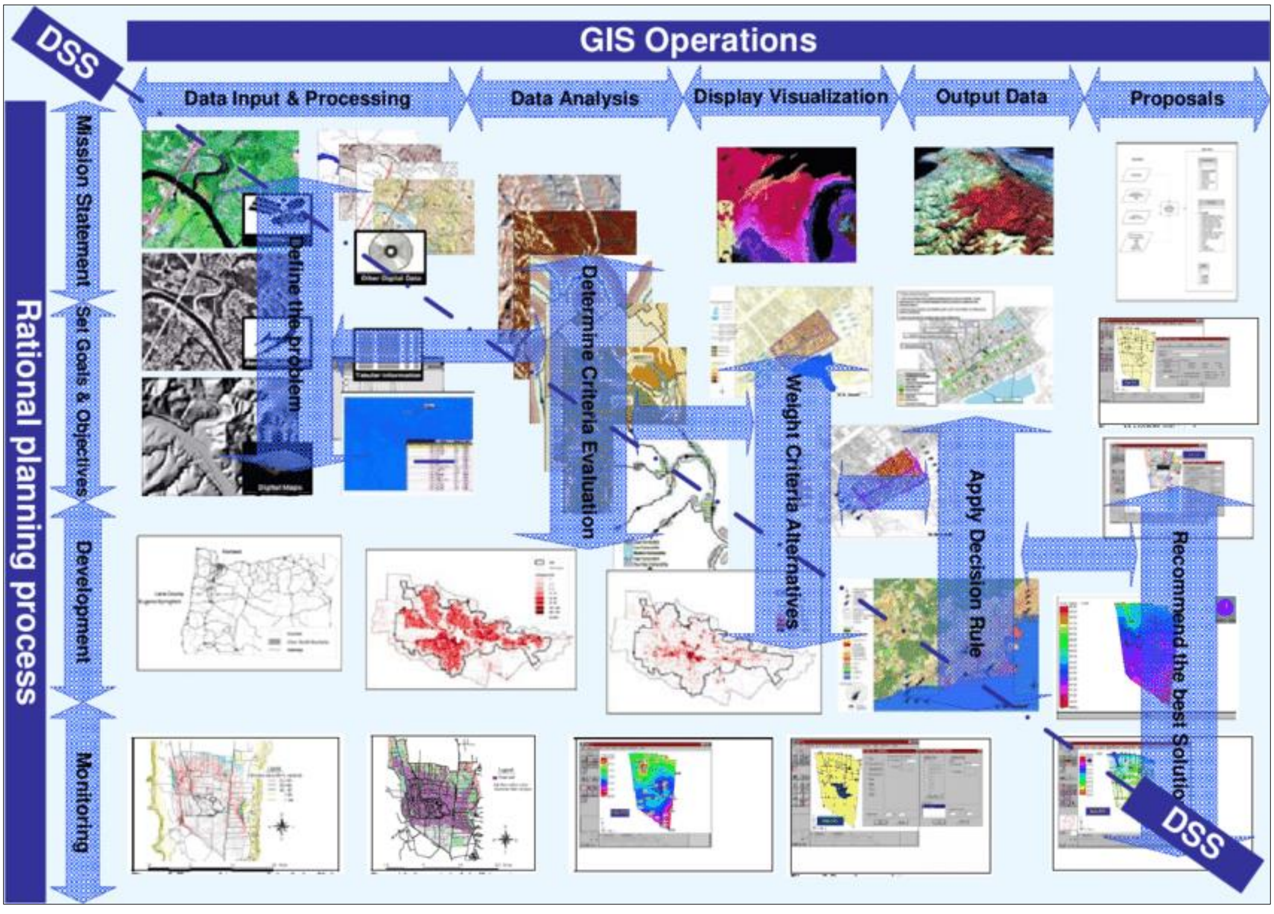

Fig 2: The interaction between the GIS, Planning Process and Decision Support System (Sultani, Soliman & Al-Hagla, 2009).

Regulatory frameworks add another layer of complexity to industrial legacy site management. Environmental regulations governing contaminated land, water quality, waste management, and human health protection vary across jurisdictions and have evolved significantly over time. Legacy sites may be subject to overlapping regulatory regimes, including national environmental protection laws, regional planning policies, and sector-specific guidelines. Compliance requirements can differ depending on current and intended land use, such as residential redevelopment, industrial reuse, or ecological restoration. Regulatory thresholds for contaminants may be revised as scientific understanding advances, altering risk classifications and intervention priorities (Aifuwa, *et al*., 2020, Bankole, Nwokediegwu & Okiye, 2020). Furthermore, liability considerations often influence decision-making, particularly where responsibility for historical contamination is disputed or shared among multiple parties. These regulatory dynamics necessitate decision-support tools that can accommodate changing standards and support transparent justification of prioritization decisions in regulatory and legal contexts.

Social dimensions are equally critical in shaping the complexity of industrial legacy sites. Many such sites are located in or near communities that have experienced long-term exposure to environmental hazards, often coinciding with broader patterns of social and economic disadvantage. Community perceptions of risk, trust in institutions, and expectations regarding remediation outcomes can significantly influence intervention priorities and acceptance of proposed actions. Stakeholder interests may diverge, with residents prioritizing health protection, local authorities focusing on redevelopment and economic revitalization, and regulators emphasizing compliance and risk reduction (Faseemo, *et al*., 2009). Historical injustices associated with industrial pollution can heighten sensitivities and demand more inclusive, participatory approaches to decision-making. A geospatial decision-support system must therefore support not only technical analysis but also communication and engagement, enabling stakeholders to understand spatial risk patterns and the rationale behind intervention choices. Figure 3 shows architecture of the spatial decision support system (SDSS) presented by Van Cauwenbergh, Ciuró & Ahlers, 2018.

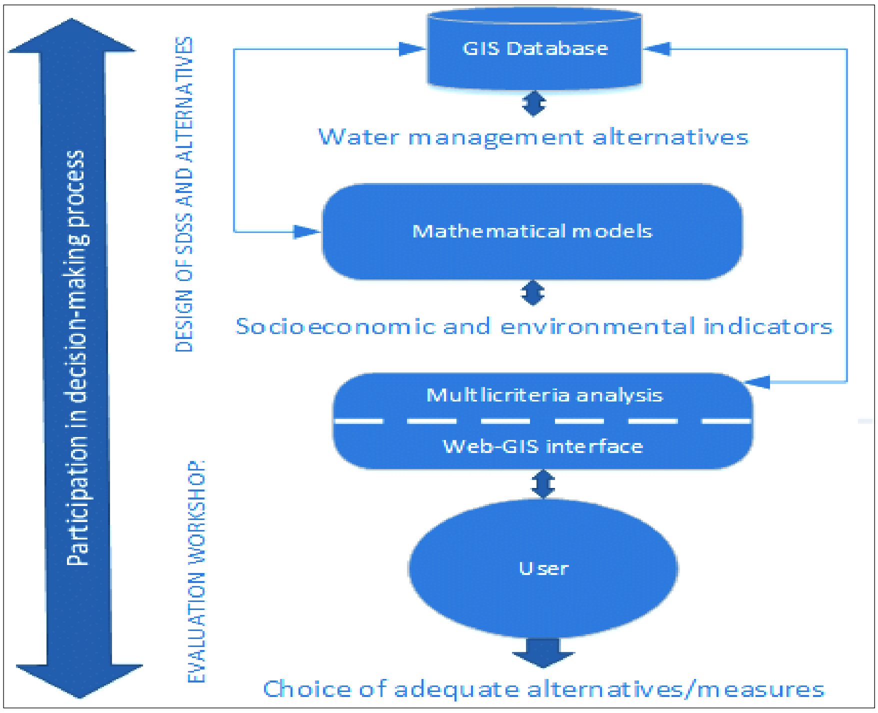

Fig 3: Architecture of the spatial decision support system (SDSS) (Van Cauwenbergh, Ciuró & Ahlers, 2018).

Land-use constraints further complicate environmental intervention planning at industrial legacy sites. Many sites occupy strategically valuable locations in urban or peri-urban areas, creating pressure to balance remediation with redevelopment objectives. Existing infrastructure, property boundaries, and ongoing activities may limit access for investigation or remediation, constraining the range of feasible interventions. In some cases, partial redevelopment has already occurred, resulting in mixed land uses that impose different protection goals and exposure scenarios within the same site. Ecologically sensitive areas, cultural heritage assets, and critical infrastructure may coexist with contaminated zones, requiring careful spatial prioritization to avoid unintended consequences (Hammed, Oshoba & Ahmed, 2019, Sanusi, *et al*., 2019). These land-use complexities reinforce the importance of spatially informed decision-making that can evaluate trade-offs and identify intervention strategies aligned with broader planning objectives.

Taken together, the context and complexity of industrial legacy sites reflect the interplay of diverse contamination sources, spatial heterogeneity, data uncertainty, regulatory obligations, social considerations, and land-use dynamics. These factors interact in ways that challenge linear or purely technical approaches to environmental intervention planning. A geospatial decision-support system offers a structured means of addressing this complexity by integrating spatial data, risk indicators, and contextual constraints into a coherent analytical framework. By grounding prioritization decisions in an explicit understanding of site context and complexity, such systems can support more equitable, transparent, and effective environmental management of industrial legacy landscapes.

4. Geospatial Decision-Support System Conceptual Design

The conceptual design of a Geospatial Decision-Support System (GDSS) for prioritizing environmental interventions in complex industrial legacy sites is founded on the need to manage spatially distributed risks, fragmented datasets, and competing decision objectives within a coherent and transparent analytical environment. Such a system must move beyond conventional mapping tools to function as an integrated decision platform that supports evidence-based prioritization under conditions of uncertainty. At its core, the GDSS is conceived as a modular, layered architecture in which data acquisition, analytical processing, decision logic, and user interaction are functionally distinct yet tightly interconnected. This design philosophy enables systematic handling of complexity while preserving flexibility for site-specific adaptation and future enhancement (Fasasi, Adebowale & Nwokediegwu, 2019, Owulade, *et al*., 2019).

The overall system architecture typically comprises four interrelated layers: a data layer, an analytical layer, a decision-support layer, and a visualization and interaction layer. The data layer serves as the foundation of the system, responsible for ingesting and managing diverse spatial and non-spatial datasets relevant to industrial legacy sites. These may include geospatial information on soil and groundwater contamination, hydrogeological conditions, land use and zoning, infrastructure networks, ecological receptors, demographic vulnerability, and regulatory boundaries. Data from multiple sources are standardized, georeferenced, and stored within a spatial database designed to accommodate varying levels of resolution and quality. Metadata management is an essential component of this layer, ensuring transparency regarding data provenance, uncertainty, and temporal relevance (Ahmed, Odejobi & Oshoba, 2020, Giwah, *et al*., 2020). By structuring data in a flexible yet rigorous manner, the GDSS establishes a reliable basis for subsequent analysis and decision-making.

Building upon this foundation, the analytical layer performs spatial processing and modeling functions that transform raw data into meaningful indicators of environmental risk and intervention relevance. Spatial analysis techniques such as overlay analysis, interpolation, buffering, and network analysis are employed to represent contaminant distributions, exposure pathways, and spatial relationships among environmental and socio-economic variables (Gober & Kirkwood, 2010, Mark, *et al*., 2010). This layer may also incorporate process-based or statistical models to simulate contaminant transport, assess exposure scenarios, or estimate ecological and human health impacts. Importantly, the analytical layer is designed to accommodate data uncertainty and heterogeneity, allowing for the incorporation of probabilistic representations, sensitivity analyses, and scenario testing (Bayeroju, *et al*., 2019, Fasasi, *et al*., 2019). Rather than producing a single deterministic outcome, the system supports exploration of alternative assumptions and data configurations, reflecting the realities of decision-making in complex industrial legacy contexts. Figure 4 shows GIS approach in spatial decision making for industrial site selection presented by Rikalovic, Cosic & Lazarevic, 2014.

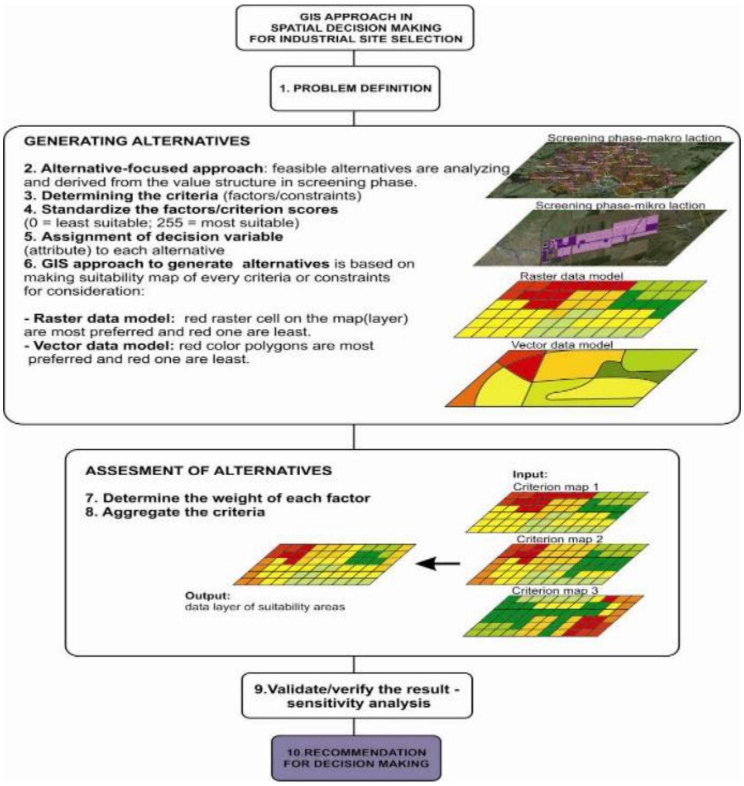

Fig 4: GIS approach in spatial decision making for industrial site selection (Rikalovic, Cosic & Lazarevic, 2014).

The decision-support layer represents the core innovation of the GDSS by linking spatial analysis outputs to structured decision logic. This layer integrates multi-criteria decision analysis techniques to evaluate and rank intervention options or spatial units based on a set of defined criteria. Criteria may include contamination severity, exposure potential, population vulnerability, ecological sensitivity, technical feasibility, cost considerations, and alignment with regulatory or land-use objectives. Each criterion is operationalized through spatial indicators derived from the analytical layer and normalized to enable comparison across heterogeneous dimensions. Weighting schemes, informed by expert judgment, stakeholder input, or policy priorities, are applied to reflect the relative importance of different criteria (Afolabi, *et al*., 2020, Fasasi, *et al*., 2020). The aggregation of weighted criteria yields composite prioritization scores that provide a transparent basis for comparing intervention needs across complex spatial landscapes. By embedding decision logic within the geospatial framework, the GDSS ensures that prioritization outcomes are directly traceable to underlying data and assumptions.

The integration of spatial analysis and decision-support logic is a defining feature of the conceptual design, distinguishing the GDSS from conventional geographic information systems or standalone decision models. Rather than treating spatial analysis and decision-making as sequential or separate processes, the system is designed to support iterative interaction between these components. Decision-makers can adjust criteria weights, modify thresholds, or explore alternative scenarios and immediately observe the spatial implications of these changes (Langat, Kumar & Koech, 2017, Nashwan, *et al*., 2018). This dynamic feedback loop enhances learning and supports more informed deliberation, particularly in settings where trade-offs among competing objectives are unavoidable. The close coupling of spatial and decision-support functions also facilitates communication among interdisciplinary teams, enabling technical experts, planners, and regulators to engage with the same analytical outputs while interpreting them through their respective perspectives (Ahmed, Odejobi & Oshoba, 2019, Nwokediegwu, Bankole & Okiye, 2019).

Scalability is a critical consideration in the conceptual design of a GDSS intended for application across diverse industrial legacy sites. The system must be capable of functioning at multiple spatial scales, from localized site assessments to regional or national prioritization exercises. This is achieved through a modular design that allows components to be activated or simplified depending on data availability and decision context. For small or data-limited sites, the system may rely on a reduced set of indicators and coarser spatial resolution, while larger or better-characterized sites can support more detailed analyses and complex modeling. The use of standardized data structures and interoperable formats facilitates integration with external datasets and platforms, enabling the GDSS to evolve alongside advances in monitoring technologies and data collection practices (Hanson, *et al*., 2012, Wagesho, 2014).

Adaptability to different site conditions is equally central to the system's conceptual design. Industrial legacy sites vary widely in their contamination profiles, regulatory contexts, stakeholder landscapes, and redevelopment trajectories. The GDSS is therefore designed as a configurable framework rather than a rigid template, allowing users to customize criteria sets, weighting schemes, and analytical methods to reflect site-specific priorities and constraints. This adaptability is further supported by the system's capacity to incorporate new data, update models, and revise decision logic as conditions change or additional information becomes available. Such adaptability aligns with principles of adaptive management, recognizing that environmental intervention planning is an ongoing process rather than a one-time exercise (Awe, Akpan & Adekoya, 2017, Osabuohien, 2017).

In sum, the conceptual design of a Geospatial Decision-Support System for prioritizing environmental interventions in complex industrial legacy sites emphasizes integration, transparency, and flexibility. By combining a robust system architecture with tightly coupled spatial analysis and decision-support logic, the GDSS provides a structured yet adaptable platform for navigating the multifaceted challenges of legacy site management. Its scalable and configurable design ensures relevance across a wide range of contexts, supporting more rational, defensible, and responsive environmental decision-making in the face of complexity and uncertainty (Leibowitz, *et al*., 2014, Ribeiro Neto, *et al*., 2014).

5. Data Sources, Integration, and Spatial Modeling Framework

The effectiveness of a Geospatial Decision-Support System for prioritizing environmental interventions in complex industrial legacy sites is fundamentally dependent on the quality, diversity, and integration of the data that underpin its analytical processes. Industrial legacy sites are shaped by long and often fragmented histories of land use, contamination, and socio-economic transformation, requiring a data framework capable of capturing both environmental processes and human dimensions in a spatially explicit manner. The data sources and integration strategy therefore form the backbone of the decision-support system, enabling the translation of heterogeneous information into coherent spatial insights that inform prioritization decisions (Akpan, Awe & Idowu, 2019, Ogundipe, *et al*., 2019).

Geospatial data inputs provide the spatial reference framework within which all other information is organized and analyzed. These typically include high-resolution base maps, topography and digital elevation models, cadastral boundaries, infrastructure networks, hydrological features, and land-use and land-cover datasets. Such geospatial layers define the physical context of industrial legacy sites and support the delineation of analysis units such as grids, parcels, or management zones. Environmental data inputs capture the nature and extent of contamination and associated risks, encompassing soil and groundwater contaminant concentrations, surface water quality indicators, sediment contamination, air quality measurements, and ecological receptor distributions (Awe & Akpan, 2017). These data may be derived from field sampling campaigns, historical monitoring records, remote sensing products, or regulatory databases. Socio-economic data inputs add a critical human dimension to the analysis, incorporating information on population density, demographic vulnerability, sensitive land uses such as schools or healthcare facilities, economic activity, and redevelopment potential. Together, these geospatial, environmental, and socio-economic datasets enable a multidimensional representation of risk and opportunity across industrial legacy landscapes (Nelitz, Boardley & Smith, 2013, Perra, *et al*., 2018).

The integration of such diverse data sources presents significant challenges, as datasets often differ in format, scale, resolution, temporal coverage, and quality. Data preprocessing is therefore a crucial step in the spatial modeling framework, aimed at transforming raw inputs into analytically compatible forms. This process typically begins with data cleaning to address missing values, inconsistencies, and errors that may arise from measurement limitations or historical record gaps. Environmental datasets may require outlier analysis to distinguish true contamination hotspots from anomalous measurements, while socio-economic data may need adjustment to reflect current conditions or align with spatial units of analysis (Akpan, *et al*., 2017, Oni, *et al*., 2018). The explicit documentation of data uncertainty during preprocessing is essential, as it informs subsequent modeling and decision-support stages.

Standardization is another key component of data integration, ensuring that disparate datasets can be meaningfully compared and combined. Spatial standardization involves transforming all datasets into a common coordinate reference system and spatial resolution, enabling accurate overlay and spatial analysis. Attribute standardization addresses differences in measurement units, value ranges, and data scales across variables. For example, contaminant concentrations, population density, and land-use suitability scores may be normalized using statistical or rule-based methods to produce dimensionless indicators suitable for multi-criteria analysis. Temporal standardization may also be required, particularly where datasets span different periods or reflect changing site conditions (Akomea-Agyin & Asante, 2019, Awe, 2017, Osabuohien, 2019). By systematically standardizing data inputs, the decision-support system establishes a consistent analytical foundation that supports transparent and reproducible prioritization outcomes.

Spatial alignment is closely related to standardization and involves the harmonization of data layers to a common spatial framework. This may entail resampling raster datasets, aggregating or disaggregating vector data, and reconciling mismatches between administrative boundaries and environmental features. The choice of spatial unit is a critical design decision, influencing both analytical resolution and computational efficiency. Grid-based approaches offer uniform coverage and are well-suited to continuous environmental variables, while parcel-based or zone-based units may better reflect regulatory or land-use considerations (Viviroli, *et al*., 2011, Watts, *et al*., 2015). In many cases, a hybrid approach is adopted, allowing the system to operate across multiple spatial representations depending on the decision context. Accurate spatial alignment ensures that interactions among data layers are correctly represented, minimizing analytical artifacts and enhancing the reliability of model outputs.

Once data inputs are preprocessed, standardized, and aligned, the spatial modeling framework governs how these layers interact to generate decision-relevant indicators. Spatial modeling in the GDSS is designed to capture the relationships among contamination sources, environmental pathways, and receptors within a spatially explicit context. Overlay analysis is a foundational mechanism, enabling the combination of multiple layers to identify areas of co-occurring risk factors, such as high contaminant concentrations overlapping with vulnerable populations or sensitive ecosystems (Edwards, *et al*., 2012, Green, 2016). Proximity and buffering analyses are used to represent exposure pathways and influence zones, while interpolation methods support the estimation of contaminant distributions in areas with sparse monitoring data. Where appropriate, network-based models may be applied to represent contaminant transport through surface water systems or infrastructure corridors.

Layer interaction mechanisms extend beyond simple overlays to incorporate weighted combinations and conditional logic that reflect decision criteria. For example, contaminant severity layers may be weighted more heavily in areas designated for residential redevelopment, while ecological sensitivity may dominate prioritization in conservation zones. Conditional rules can be applied to exclude or flag areas where interventions are technically infeasible or restricted by regulatory constraints. The modeling framework may also support scenario analysis, allowing users to explore how changes in land use, regulatory thresholds, or remediation assumptions affect spatial prioritization outcomes. Such mechanisms enable the GDSS to function as an exploratory as well as evaluative tool, supporting adaptive decision-making under uncertainty (Field, 2012, McMillan, *et al*., 2016).

Uncertainty is an inherent feature of spatial modeling at industrial legacy sites and is explicitly addressed within the framework through sensitivity analysis and probabilistic representations. Alternative data assumptions, weighting schemes, or model parameters can be tested to assess their influence on prioritization results, providing insight into the robustness of decision-support outputs. This capacity to examine uncertainty strengthens the credibility of the system and supports more informed risk communication with stakeholders and regulators (Hubbard, *et al*., 2018, Singh, van Werkhoven & Wagener, 2014).

In summary, the data sources, integration processes, and spatial modeling framework of a Geospatial Decision-Support System form an interconnected foundation that enables effective prioritization of environmental interventions in complex industrial legacy sites. By systematically integrating geospatial, environmental, and socio-economic data through rigorous preprocessing, standardization, and spatial alignment, the system transforms fragmented information into coherent spatial representations of risk and opportunity. The spatial modeling and layer interaction mechanisms then translate these representations into decision-relevant insights, supporting transparent, adaptable, and defensible environmental management strategies in challenging legacy contexts.

6. Environmental Risk Indicators and Prioritization Criteria

Environmental risk indicators and prioritization criteria constitute the analytical core of a Geospatial Decision-Support System designed to guide environmental interventions in complex industrial legacy sites. These indicators translate heterogeneous environmental, social, and technical information into structured metrics that can be compared, combined, and interpreted within a spatial decision-making context. Given the multifaceted nature of industrial legacy contamination, the careful selection and operationalization of indicators are essential to ensure that prioritization outcomes reflect real-world risks, management objectives, and contextual constraints rather than arbitrary or overly simplified measures (Furniss, 2011, Handmer, *et al*., 2012).

The selection of contamination indicators is typically grounded in an understanding of the types, concentrations, and spatial distributions of pollutants associated with historical industrial activities. Indicators may represent individual contaminants of concern, such as heavy metals, hydrocarbons, or chlorinated solvents, or composite measures that summarize multiple substances based on toxicity, persistence, or regulatory thresholds. Spatial indicators of contamination severity often incorporate exceedance ratios relative to environmental standards, cumulative contamination indices, or probabilistic estimates of contaminant presence in data-sparse areas. These indicators are designed to capture not only the magnitude of contamination but also its spatial extent and potential mobility across environmental media (Kato, 2010, Meerow & Newell, 2017). In industrial legacy contexts where multiple contaminants coexist, composite contamination indicators provide a practical means of representing cumulative burden while maintaining analytical tractability.

Exposure indicators extend the analysis beyond contamination presence to consider the likelihood and pathways through which humans and ecological receptors may come into contact with pollutants. Such indicators are inherently spatial, reflecting proximity to contamination sources, land-use patterns, and environmental transport mechanisms. For human exposure, indicators may include distance-weighted measures of population density, presence of sensitive receptors such as schools or healthcare facilities, and modeled exposure pathways through groundwater abstraction or food chains. Ecological exposure indicators may incorporate habitat overlap, species sensitivity, or connectivity to downstream ecosystems (Jayasooriya, 2016, Sayles, 2017). By explicitly representing exposure pathways, these indicators help differentiate between areas of high contamination that pose limited immediate risk and areas where even moderate contamination may result in significant adverse impacts due to exposure potential.

Vulnerability indicators introduce a socio-environmental dimension to prioritization by accounting for differential capacity to cope with or recover from environmental harm. In the context of industrial legacy sites, vulnerability may reflect socio-economic disadvantage, health status, access to resources, or dependence on affected environmental services. Spatial vulnerability indicators may be derived from demographic data, indices of deprivation, or land-use characteristics that influence susceptibility to contamination impacts (Ferdinand & Yu, 2016, Koop & van Leeuwen, 2017). Incorporating vulnerability into prioritization criteria aligns the decision-support system with principles of environmental justice and equitable risk management, ensuring that interventions are not solely driven by contamination levels but also by the potential for disproportionate harm.

Once contamination, exposure, and vulnerability indicators are selected, the challenge lies in combining them in a manner that is analytically sound and transparent. Weighting schemes are employed to reflect the relative importance of different indicators or indicator groups in the prioritization process. Weight selection may be informed by regulatory requirements, expert judgment, stakeholder consultation, or policy objectives, and it is often one of the most sensitive aspects of decision-support system design. Simple equal-weighting approaches offer transparency and ease of interpretation but may inadequately reflect real-world priorities. Conversely, differentiated weighting schemes can better capture nuanced decision contexts but introduce subjectivity and potential bias. To address this tension, many systems adopt participatory or multi-method weighting approaches, combining expert elicitation, analytic hierarchy processes, or sensitivity analysis to justify and test weighting choices (Boriana, 2017, Hou & Al-Tabbaa, 2014).

Normalization approaches are essential to enable meaningful aggregation of indicators measured on different scales and units. Without normalization, indicators such as contaminant concentration, population density, and socio-economic indices cannot be directly compared or combined. Common normalization techniques include min–max scaling, z-score standardization, and threshold-based scoring relative to regulatory or risk benchmarks (Cheng, *et al*., 2011, Herat & Agamuthu, 2012). The choice of normalization method influences the relative influence of extreme values and should be carefully matched to the decision context. For example, threshold-based normalization may be appropriate where regulatory exceedances trigger mandatory intervention, while continuous scaling may better represent gradations of risk in prioritization exercises. Explicit documentation of normalization choices enhances transparency and supports reproducibility of prioritization outcomes.

Criteria aggregation represents the final step in translating individual indicators into a coherent ranking of intervention priorities. Aggregation methods range from simple additive models to more complex multi-criteria decision analysis techniques that account for interactions and trade-offs among criteria. Additive weighted sum models are commonly used due to their interpretability and computational simplicity, producing composite scores that can be mapped and compared across spatial units. More advanced approaches may incorporate non-compensatory rules, ensuring that high performance on one criterion does not fully offset poor performance on another, particularly where minimum standards must be met (Mitchell, 2012, Sweeney & Kabouris, 2017). The aggregation process is designed to preserve traceability, allowing decision-makers to decompose composite scores and understand the contribution of individual indicators to overall rankings.

The resulting intervention ranking provides a spatially explicit representation of relative priority across industrial legacy sites or within a single site. High-priority areas are those where contamination severity, exposure potential, and vulnerability converge, indicating a strong case for immediate or intensive intervention. Lower-priority areas may still require monitoring or long-term management but are differentiated based on comparative risk and impact considerations. Importantly, prioritization outputs are not intended to replace professional judgment or regulatory decision-making but to support them by providing a structured, evidence-based foundation for deliberation (Cappuyns & Kessen, 2014, Williamson, *et al*., 2011).

In conclusion, environmental risk indicators and prioritization criteria are central to the functioning of a Geospatial Decision-Support System for complex industrial legacy sites. Through careful selection of contamination, exposure, and vulnerability indicators, transparent weighting and normalization approaches, and robust criteria aggregation methods, the system translates complex spatial data into actionable insights. This structured approach enhances the consistency, defensibility, and equity of environmental intervention prioritization, supporting more effective management of industrial legacy risks under conditions of complexity and uncertainty.

7. Decision Algorithms, Uncertainty Handling, and Sensitivity Analysis

Decision algorithms form the analytical engine of a Geospatial Decision-Support System designed to prioritize environmental interventions in complex industrial legacy sites. These algorithms provide a structured means of synthesizing diverse spatial indicators, reconciling competing objectives, and producing defensible prioritization outcomes under conditions of uncertainty. Given the heterogeneous nature of legacy contamination, decision algorithms must balance analytical rigor with transparency and usability, enabling decision-makers to understand not only the results but also the logic and assumptions that underpin them (Hardie & McKinley, 2014, Williamson, 2011).

Multi-criteria decision analysis techniques are widely employed within geospatial decision-support systems to address the inherently multi-dimensional nature of environmental intervention planning. Industrial legacy sites present simultaneous concerns related to contamination severity, exposure pathways, population vulnerability, ecological sensitivity, technical feasibility, and cost considerations, none of which can be reduced to a single metric without loss of critical information. Multi-criteria decision analysis provides a formal framework for integrating these diverse criteria into a coherent prioritization structure. Common techniques include weighted linear combination, analytic hierarchy process, outranking methods, and compromise programming. Weighted linear combination is particularly well-suited to spatial applications due to its computational efficiency and interpretability, allowing normalized and weighted indicators to be aggregated into composite priority scores (An, *et al*., 2016, Mgbeahuruike, 2018). Analytic hierarchy process supports structured weight elicitation through pairwise comparisons, facilitating stakeholder involvement and enhancing transparency in how priorities are defined. Outranking methods, such as ELECTRE or PROMETHEE, may be applied where decision contexts require explicit handling of trade-offs and non-compensatory relationships among criteria, ensuring that critical thresholds are respected.

The selection and implementation of decision algorithms are closely linked to the treatment of data gaps and uncertainty, which are unavoidable in industrial legacy site contexts. Historical monitoring data are often incomplete, unevenly distributed, or collected using inconsistent methodologies, resulting in spatial and temporal uncertainty that can significantly influence prioritization outcomes. A robust geospatial decision-support system must therefore incorporate mechanisms for representing and propagating uncertainty throughout the analytical process rather than treating it as an external limitation (Lemming, 2010, Wang, *et al*., 2017). One approach involves the explicit characterization of data quality through confidence scores or uncertainty ranges associated with individual indicators. These measures can be integrated into decision algorithms by adjusting indicator weights, modifying aggregation rules, or producing probabilistic rather than deterministic prioritization outputs.

Spatial interpolation and modeling techniques are commonly used to address data gaps, particularly for environmental variables such as contaminant concentrations or groundwater conditions. However, such techniques introduce their own uncertainties, which must be acknowledged and quantified. Geospatial decision-support systems often incorporate multiple interpolation methods or model scenarios to explore the implications of alternative assumptions. Probabilistic overlays and stochastic simulations may be employed to generate distributions of possible prioritization outcomes rather than single-point estimates, providing a richer representation of uncertainty (Ahmed, 2017, Karpatne, *et al*., 2018). In data-limited settings, scenario-based approaches allow decision-makers to compare conservative, moderate, and optimistic assumptions regarding contamination extent or exposure potential, supporting precautionary yet flexible intervention planning.

Uncertainty propagation is a critical consideration in the design of decision algorithms, as uncertainties in input data and model parameters can interact in complex ways. Geospatial decision-support systems address this challenge by systematically tracking how uncertainty in individual indicators influences aggregated prioritization scores. Monte Carlo simulation techniques are particularly useful in this regard, enabling repeated sampling of uncertain parameters to produce probability distributions of outcomes. Such analyses help identify areas where prioritization rankings are robust across a wide range of assumptions and areas where rankings are highly sensitive to specific inputs (Liakos, *et al*., 2018, Singh, Gupta & Mohan, 2014). This information is invaluable for directing additional data collection efforts and for communicating confidence levels to stakeholders and regulators.

Sensitivity analysis serves as a complementary tool to uncertainty handling by explicitly examining how changes in decision assumptions affect prioritization results. Sensitivity testing may involve systematic variation of indicator weights, normalization methods, or decision thresholds to assess their influence on spatial rankings. In the context of industrial legacy sites, sensitivity analysis is especially important given the potential subjectivity associated with weighting schemes and the high stakes of intervention decisions. By revealing which criteria exert the greatest influence on prioritization outcomes, sensitivity analysis enhances transparency and supports more informed deliberation among decision-makers (Naghibi, Pourghasemi & Dixon, 2016, Rodriguez-Galiano, *et al*., 2014).

Different forms of sensitivity analysis can be employed depending on the decision context and system complexity. Local sensitivity analysis focuses on small perturbations around baseline assumptions, identifying criteria or parameters to which results are most responsive. Global sensitivity analysis explores a broader range of parameter combinations, providing insight into interactions among criteria and potential nonlinear effects. Visual tools such as sensitivity maps or ranking stability plots are often integrated into the geospatial decision-support system to communicate these findings in an intuitive manner (Park, *et al*., 2016, Ransom, *et al*., 2017). These visualizations enable users to identify spatial units where prioritization is stable versus those where rankings shift significantly under alternative assumptions.

The integration of decision algorithms, uncertainty handling, and sensitivity analysis supports adaptive decision-making in complex industrial legacy environments. Rather than producing a single definitive ranking, the geospatial decision-support system provides a spectrum of insights that reflect the inherent uncertainty and complexity of the problem. This approach aligns with best practices in environmental risk management, which emphasize iterative learning, precaution, and stakeholder engagement. Decision-makers can use prioritization outputs to identify high-confidence intervention zones, flag areas requiring further investigation, and explore trade-offs among competing objectives (Barzegar, *et al*., 2018, Karandish, Darzi-Naftchali & Asgari, 2017).

In conclusion, decision algorithms, uncertainty handling, and sensitivity analysis are central to the credibility and effectiveness of a Geospatial Decision-Support System for prioritizing environmental interventions in complex industrial legacy sites. Through the application of multi-criteria decision analysis techniques, explicit treatment of data gaps and uncertainty propagation, and rigorous sensitivity testing, the system transforms complex and uncertain information into actionable decision support. This integrated approach enhances transparency, robustness, and accountability, enabling more rational and resilient environmental intervention strategies in challenging legacy contexts.

8. Visualization Outputs, Decision Workflows, and Stakeholder Use

Visualization outputs, decision workflows, and stakeholder use represent the interface through which a Geospatial Decision-Support System (GDSS) translates complex analytical processes into actionable knowledge for environmental intervention planning at industrial legacy sites. While data integration, modeling, and decision algorithms operate largely in the background, visualization and workflow design determine whether the system effectively supports real-world decision-making. In complex legacy contexts characterized by technical uncertainty, regulatory scrutiny, and diverse stakeholder interests, the clarity, accessibility, and credibility of system outputs are as critical as analytical rigor (Burritt, Schaltegger & Zvezdov, 2011, Gibassier & Schaltegger, 2015).

Mapping is the primary visualization mechanism through which spatial risk patterns and prioritization outcomes are communicated. Spatial maps enable users to immediately perceive the geographic distribution of contamination severity, exposure potential, vulnerability, and composite intervention priorities. These maps are typically layered, allowing users to toggle between individual indicators and aggregated results, thereby supporting both high-level overview and detailed inspection (Ascui & Lovell, 2012, Steininger, *et al.*, 2016). Graduated color schemes, classification thresholds, and symbology are carefully designed to convey relative risk without oversimplifying underlying variability. Interactive mapping capabilities allow users to query specific locations, examine indicator values, and explore how prioritization outcomes change under different assumptions. In industrial legacy sites where contamination patterns are heterogeneous and boundaries are often contested, such spatial transparency enhances trust in the decision-support process and facilitates shared understanding among technical and non-technical audiences.

Dashboards complement spatial maps by synthesizing complex analytical outputs into structured, at-a-glance summaries that support decision comparison and monitoring. A well-designed GDSS dashboard typically integrates key performance indicators, charts, and tables that reflect prioritization criteria, uncertainty metrics, and scenario outcomes. Dashboards enable decision-makers to compare intervention zones, track changes over time as new data are incorporated, and assess the implications of alternative weighting schemes or regulatory thresholds (Ascui, 2014, Hartmann, Perego & Young, 2013). By presenting analytical results alongside metadata on data quality and uncertainty, dashboards promote informed interpretation rather than uncritical acceptance of outputs. In the context of industrial legacy sites, dashboards also support ongoing management by linking prioritization results to remediation progress, monitoring outcomes, and resource allocation decisions.

Decision matrices provide a structured representation of how prioritization outcomes relate to specific criteria and decision rules. These matrices display the contribution of contamination, exposure, vulnerability, feasibility, and other criteria to overall rankings, enabling users to trace how composite scores are derived. Decision matrices are particularly valuable in deliberative settings where trade-offs must be explicitly negotiated, such as balancing rapid risk reduction against long-term redevelopment goals. By making decision logic explicit, matrices reduce the perception of arbitrariness and support defensible justification of intervention choices. They also serve as a bridge between quantitative analysis and qualitative judgment, allowing expert insight and policy considerations to be incorporated transparently (Maas, Schaltegger & Crutzen, 2016, Tang & Luo, 2014).

The visualization outputs of a GDSS play a crucial role in supporting regulatory review processes. Environmental regulators are often required to evaluate remediation priorities, approve intervention plans, and ensure compliance with evolving standards. Spatial maps and dashboards provide regulators with a clear, evidence-based overview of how prioritization decisions align with regulatory thresholds, land-use objectives, and risk management principles. The ability to demonstrate how different criteria and assumptions influence outcomes strengthens the credibility of submissions and facilitates constructive dialogue between proponents and oversight bodies. Moreover, visualization tools support auditability by enabling regulators to examine underlying data sources, modeling assumptions, and decision rules, thereby enhancing accountability in complex legacy site management (Bowen & Wittneben, 2011, Schaltegger & Csutora, 2012).

Stakeholder communication is another critical function supported by visualization and decision workflows. Industrial legacy sites frequently affect multiple stakeholder groups, including local communities, landowners, developers, environmental organizations, and public authorities, each with distinct concerns and levels of technical expertise. Visualization outputs provide a common reference point for engagement, enabling stakeholders to understand spatial risk patterns and the rationale behind prioritization decisions (Hoek, Beelen & Brunekreef, 2011, Levy, 2013). Interactive maps and dashboards can be used in workshops or public consultations to explore scenarios collaboratively, fostering transparency and trust. By visually linking environmental risks to social and land-use contexts, the GDSS supports more inclusive decision-making and helps address concerns related to environmental justice and equity.

Integration of visualization outputs into decision workflows ensures that the GDSS is not merely an analytical tool but an operational component of planning and remediation processes. Decision workflows define how data inputs, analytical steps, review stages, and stakeholder interactions are sequenced within the system. In practice, this involves embedding the GDSS within existing environmental management frameworks, such as site investigation protocols, remediation planning cycles, and adaptive management strategies. Prioritization outputs generated by the system inform decisions on where to allocate resources for further investigation, which areas require immediate intervention, and which can be managed through monitoring or institutional controls (Derycke, *et al*., 2018, Kulawiak & Lubniewski, 2014). By aligning system outputs with established decision points, the GDSS enhances efficiency and consistency in legacy site management.

The integration of the GDSS into remediation workflows also supports iterative learning and adaptation. As interventions are implemented and new monitoring data become available, visualization tools enable users to assess changes in spatial risk patterns and update prioritization accordingly. Dashboards can track progress against intervention objectives, highlighting areas where remediation has reduced risk and areas where residual contamination persists (Roghani, 2018, Wang, Unger & Parker, 2014). This feedback loop reinforces adaptive management principles, allowing decision-makers to refine strategies in response to evolving conditions rather than relying on static plans. In complex industrial legacy sites where uncertainty is unavoidable, such adaptability is essential for long-term effectiveness.

Beyond site-specific applications, visualization outputs and decision workflows support strategic planning at broader spatial scales. Regional or national authorities can use aggregated maps and dashboards to identify clusters of high-priority legacy sites, assess cumulative impacts, and allocate funding across jurisdictions. Decision matrices facilitate comparison among sites with different contamination profiles and socio-economic contexts, supporting more equitable and transparent resource distribution. In this way, the GDSS functions not only as a technical tool but also as a governance instrument that aligns local intervention decisions with broader policy objectives (McAlary, Provoost & Dawson, 2010, Provoost, *et al*., 2013).

In summary, visualization outputs, decision workflows, and stakeholder use are central to the practical value of a Geospatial Decision-Support System for prioritizing environmental interventions in complex industrial legacy sites. Through interactive maps, dashboards, and decision matrices, the system translates complex analytical results into accessible, defensible, and decision-relevant formats (Andres, *et al*., 2018, Turczynowicz, Pisaniello & Williamson, 2012). By supporting regulatory review, stakeholder communication, and integration into planning and remediation workflows, these outputs ensure that the GDSS meaningfully informs real-world action. The effectiveness of environmental intervention prioritization ultimately depends not only on analytical sophistication but on the system's ability to communicate insights, support collaboration, and adapt to changing conditions, all of which are enabled through thoughtful visualization and workflow design.

9. Conclusion

This study has advanced a comprehensive Geospatial Decision-Support System designed to address the persistent and multifaceted challenges associated with prioritizing environmental interventions in complex industrial legacy sites. By integrating geospatial data, environmental risk indicators, socio-economic vulnerability metrics, and structured decision algorithms within a unified framework, the system provides a transparent and analytically robust basis for comparing intervention needs across heterogeneous landscapes. Its key contribution lies in demonstrating how spatial analysis and multi-criteria decision-support logic can be tightly coupled to translate fragmented and uncertain data into defensible prioritization outcomes. The system's modular architecture, explicit treatment of uncertainty, and emphasis on visualization and stakeholder engagement collectively enhance its capacity to support informed, adaptive, and context-sensitive decision-making in legacy site management.

The capabilities of the proposed system extend beyond technical risk assessment to encompass strategic planning and governance functions. By explicitly linking contamination severity, exposure pathways, and vulnerability considerations to spatially resolved intervention rankings, the system supports more rational allocation of limited remediation resources. Its ability to accommodate data-limited conditions, incorporate evolving regulatory thresholds, and explore alternative scenarios strengthens decision resilience in the face of uncertainty. The use of interactive maps, dashboards, and decision matrices ensures that complex analytical outputs are accessible to regulators, planners, and affected communities, fostering transparency and shared understanding. These features position the system as a practical tool for bridging the gap between scientific analysis and policy-relevant decision-making.

From an environmental management and policy perspective, the adoption of a geospatial decision-support system has significant implications. It enables a shift from reactive, site-by-site remediation approaches toward more strategic, risk-based prioritization aligned with broader sustainability and land-use objectives. By making decision logic explicit and auditable, the system supports regulatory accountability and facilitates compliance with environmental standards while accommodating competing socio-economic goals. Importantly, the inclusion of vulnerability indicators enhances the potential for more equitable environmental governance, ensuring that intervention priorities reflect not only contamination levels but also the distribution of risks and benefits across communities. At a policy level, such systems can inform funding allocation, regional planning, and the development of harmonized remediation strategies across jurisdictions.

Looking forward, several directions for future development and application emerge. Further refinement of uncertainty modeling, including the integration of real-time monitoring data and advanced probabilistic techniques, could enhance the system's predictive and adaptive capabilities. Expanding interoperability with emerging digital platforms, such as digital twins and open environmental data infrastructures, would support broader scalability and integration into national and international policy frameworks. Additionally, deeper incorporation of participatory tools could strengthen stakeholder engagement and legitimacy, particularly in contexts characterized by historical environmental injustice. As industrial legacy challenges continue to evolve under pressures of urbanization, climate change, and regulatory transformation, the continued development and application of geospatial decision-support systems offer a promising pathway toward more effective, transparent, and sustainable environmental intervention planning.

10. References

1. Afolabi M, Onukogu OA, Igunma TO, Adeleke AK, Nwokediegwu ZQS. Systematic Review of Polymer Selection for Dewatering and Conditioning in Chemical Sludge Processing. 2020.

2. Afolabi M, Onukogu OA, Igunma TO, Adeleke AK, Nwokediegwu ZQS. Advances in Process Safety and Hazard Mitigation in Chlorination and Disinfection Units of Water Treatment Plants. 2020.
3. Ahmed F. An IoT-big data based machine learning technique for forecasting water requirement in irrigation field. In: International conference on research and practical issues of enterprise information systems. Cham: Springer International Publishing; 2017. p. 67-77.
4. Ahmed KS, Odejobi OD, Oshoba TO. Algorithmic model for constraint satisfaction in cloud network resource allocation. IRE Journals. 2019;2(12):516-532.
5. Ahmed KS, Odejobi OD, Oshoba TO. Predictive model for cloud resource scaling using machine learning techniques. Journal of Frontiers in Multidisciplinary Research. 2020;1(1):173-183.
6. Aifuwa SE, Oshoba TO, Ogbuefi E, Ike PN, Nnabueze SB, Olatunde-Thorpe J. Predictive analytics models enhancing supply chain demand forecasting accuracy and reducing inventory management inefficiencies. International Journal of Multidisciplinary Research and Growth Evaluation. 2020;1(3):171-181.
7. Akomea-Agyin K, Asante M. Analysis of security vulnerabilities in wired equivalent privacy (WEP). International Research Journal of Engineering and Technology. 2019;6(1):529-536.
8. Akpan UU, Adekoya KO, Awe ET, Garba N, Oguncoker GD, Ojo SG. Mini-STRs screening of 12 relatives of Hausa origin in northern Nigeria. Nigerian Journal of Basic and Applied Sciences. 2017;25(1):48-57.
9. Akpan UU, Awe TE, Idowu D. Types and frequency of fingerprint minutiae in individuals of Igbo and Yoruba ethnic groups of Nigeria. Ruhuna Journal of Science. 2019;10(1).
10. An CJ, McBean E, Huang GH, Yao Y, Zhang P, Chen XJ, *et al*. Multi-soil-layering systems for wastewater treatment in small and remote communities. J Environ Inform. 2016;27(2):131-144.
11. Andres L, Boateng K, Borja-Vega C, Thomas E. A review of in-situ and remote sensing technologies to monitor water and sanitation interventions. Water. 2018;10(6):756.
12. Asante M, Akomea-Agyin K. Analysis of security vulnerabilities in wifi-protected access pre-shared key. 2019.
13. Ascui F. A review of carbon accounting in the social and environmental accounting literature: what can it contribute to the debate? Social and Environmental Accountability Journal. 2014;34(1):6-28.
14. Ascui F, Lovell H. Carbon accounting and the construction of competence. Journal of Cleaner Production. 2012;36:48-59.
15. Awe ET. Hybridization of snout mouth deformed and normal mouth African catfish Clarias gariepinus. Animal Research International. 2017;14(3):2804-2808.
16. Awe ET, Akpan UU. Cytological study of Allium cepa and Allium sativum. 2017.
17. Awe ET, Akpan UU, Adekoya KO. Evaluation of two MiniSTR loci mutation events in five Father-Mother-Child trios of Yoruba origin. Nigerian Journal of Biotechnology. 2017;33:120-124.
18. Bankole AO, Nwokediegwu ZS, Okiye SE. Emerging cementitious composites for 3D printed interiors and exteriors: A materials innovation review. Journal of Frontiers in Multidisciplinary Research. 2020;1(1):127-144. ISSN: 3050-9726.
19. Barzegar R, Moghaddam AA, Deo R, Fijani E, Tziritis E. Mapping groundwater contamination risk of multiple aquifers using multi-model ensemble of machine learning algorithms. Science of the Total Environment. 2018;621:697-712.
20. Bayeroju OF, Sanusi AN, Queen Z, Nwokediegwu S. Bio-Based Materials for Construction: A Global Review of Sustainable Infrastructure Practices. 2019.
21. Boriana V. Urban Regeneration of Underused Industrial Sites in Albania [Doctoral dissertation]. 2017.
22. Bowen F, Wittneben B. Carbon accounting: Negotiating accuracy, consistency and certainty across organisational fields. Accounting, Auditing & Accountability Journal. 2011;24(8):1022-1036.
23. Burritt RL, Schaltegger S, Zvezdov D. Carbon management accounting: explaining practice in leading German companies. Australian Accounting Review. 2011;21(1):80-98.
24. Cappuyns V, Kessen B. Combining life cycle analysis, human health and financial risk assessment for the evaluation of contaminated site remediation. Journal of Environmental Planning and Management. 2014;57(7):1101-1121.
25. Cheng F, Geertman S, Kuffer M, Zhan Q. An integrative methodology to improve brownfield redevelopment planning in Chinese cities: A case study of Futian, Shenzhen. Computers, Environment and Urban Systems. 2011;35(5):388-398.
26. Derycke V, Coftier A, Zornig C, Leprond H, Scamps M, Gilbert D. Environmental assessments on schools located on or near former industrial facilities: Feedback on attenuation factors for the prediction of indoor air quality. Science of the Total Environment. 2018;626:754-761.
27. Edwards FK, Baker R, Dunbar M, Laizé C. A review of the processes and effects of droughts and summer floods in rivers and threats due to climate change on current adaptive strategies. 2012.
28. Fasasi ST, Adebowale OJ, Nwokediegwu ZQS. A techno-economic model of continuous versus intermittent methane monitoring programs. Iconic Research and Engineering Journals. 2019;2(7).
29. Fasasi ST, Adebowale OJ, Abdulsalam A, Nwokediegwu ZQS. Benchmarking performance metrics of methane monitoring technologies in simulated environments. Iconic Research and Engineering Journals. 2019;3(3):193-202.
30. Fasasi ST, Adebowale OJ, Abdulsalam A, Nwokediegwu ZQS. Design framework for continuous monitoring systems in industrial methane surveillance. Iconic Research and Engineering Journals. 2020;4(1):280-288.
31. Fasasi ST, Adebowale OJ, Abdulsalam A, Nwokediegwu ZQS. Time-series modeling of methane emission events using machine learning forecasting algorithms. IRE Journals. 2020;4(4):337-346.
32. Fasasi ST, Adebowale OJ, Abdulsalam A, Nwokediegwu ZQS. Atmospheric plume dispersion modeling for methane quantification under variable conditions. IRE Journals. 2020;3(8):353-362.
33. Fasasi S, Ekechi AT. Conceptual framework for process optimization in gas turbine performance and energy

efficiency. International Journal of Multidisciplinary Futuristic Development. 2020;1(2):138-153.

34. Fasasi S, Ekechi AT. Conceptual model for regeneration of biodiesel from agricultural feedstock and waste materials. International Journal of Multidisciplinary Futuristic Development. 2020;1(2):138-153.
35. Faseemo O, Massot J, Essien N, Healy W, Owah E. Multidisciplinary Approach to Optimising Hydrocarbon Recovery From Conventional Offshore Nigeria: OML100 Case Study. In: SPE Nigeria Annual International Conference and Exhibition. SPE; 2009. SPE-128889.
36. Ferdinand AV, Yu D. Sustainable urban redevelopment: Assessing the impact of third-party rating systems. Journal of Urban Planning and Development. 2016;142(1):05014033.
37. Field CB, editor. Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change. Cambridge University Press; 2012.
38. Furniss MJ. Water, climate change, and forests: watershed stewardship for a changing climate. DIANE Publishing; 2011.
39. Gibassier D, Schaltegger S. Carbon management accounting and reporting in practice: a case study on converging emergent approaches. Sustainability Accounting, Management and Policy Journal. 2015;6(3):340-365.
40. Giwah ML, Nwokediegwu ZS, Etukudoh EA, Gbabo EY. A resilient infrastructure financing framework for renewable energy expansion in Sub-Saharan Africa. IRE Journals. 2020;3(12):382-394. Available from: https://www.irejournals.com/paper-details/1709804.
41. Giwah ML, Nwokediegwu ZS, Etukudoh EA, Gbabo EY. A systems thinking model for energy policy design in Sub-Saharan Africa. IRE Journals. 2020;3(7):313-324. Available from: https://www.irejournals.com/paper-details/1709803.
42. Giwah ML, Nwokediegwu ZS, Etukudoh EA, Gbabo EY. Sustainable energy transition framework for emerging economies: Policy pathways and implementation gaps. International Journal of Multidisciplinary Evolutionary Research. 2020;1(1):1-6. doi:10.54660/IJMER.2020.1.1.01-06.
43. Gober P, Kirkwood CW. Vulnerability assessment of climate-induced water shortage in Phoenix. Proceedings of the National Academy of Sciences. 2010;107(50):21295-21299.
44. Green TR. Linking climate change and groundwater. In: Integrated groundwater management: Concepts, approaches and challenges. Cham: Springer International Publishing; 2016. p. 97-141.
45. Hammed NI, Oshoba TO, Ahmed KS. Hybrid cloud strategy model for cost-optimized deployment in regulated industries. IRE Journals. 2019;3(2):932-948.
46. Handmer J, Honda Y, Kundzewicz ZW, Arnell N, Benito G, Hatfield J, *et al*. Changes in impacts of climate extremes: human systems and ecosystems. In: Managing the risks of extreme events and disasters to advance climate change adaptation special report of the intergovernmental panel on climate change. 2012. p. 231-290.
47. Hanson RT, Flint LE, Flint AL, Dettinger MD, Faunt CC, Cayan D, *et al*. A method for physically based model analysis of conjunctive use in response to potential climate changes. Water Resources Research. 2012;48(6).
48. Hardie SML, McKinley IG. Fukushima remediation: status and overview of future plans. Journal of Environmental Radioactivity. 2014;133:75-85.
49. Hartmann F, Perego P, Young A. Carbon accounting: Challenges for research in management control and performance measurement. Abacus. 2013;49(4):539-563.
50. Herat S, Agamuthu P. E-waste: a problem or an opportunity? Review of issues, challenges and solutions in Asian countries. Waste Management & Research. 2012;30(11):1113-1129.
51. Hoek G, Beelen R, Brunekreef B. Methodological issues and statistical analysis in land use regression modeling. Epidemiology. 2011;22(1):S101.
52. Hou D, Al-Tabbaa A. Sustainability: A new imperative in contaminated land remediation. Environmental Science & Policy. 2014;39:25-34.
53. Hubbard SS, Williams KH, Agarwal D, Banfield J, Beller H, Bouskill N, *et al*. The East River, Colorado, Watershed: A mountainous community testbed for improving predictive understanding of multiscale hydrological–biogeochemical dynamics. Vadose Zone Journal. 2018;17(1):1-25.
54. Ike PN, Aifuwa SE, Nnabueze SB, Olatunde-Thorpe J, Ogbuefi E, Oshoba TO, *et al*. Utilizing Nanomaterials in Healthcare Supply Chain Management for Improved Drug Delivery Systems. 2018;12:13.
55. Jayasooriya VM. Optimization of green infrastructure practices for industrial areas [Doctoral dissertation]. Victoria University; 2016.
56. Karandish F, Darzi-Naftchali A, Asgari A. Application of machine-learning models for diagnosing health hazard of nitrate toxicity in shallow aquifers. Paddy and Water Environment. 2017;15(1):201-215.
57. Karpatne A, Ebert-Uphoff I, Ravela S, Babaie HA, Kumar V. Machine learning for the geosciences: Challenges and opportunities. IEEE Transactions on Knowledge and Data Engineering. 2018;31(8):1544-1554.
58. Kato S. Greenspace conservation planning framework for urban regions based on a forest bird-habitat relationship study and the resilience thinking [Doctoral dissertation]. University of Massachusetts Amherst; 2010.
59. Koop SH, van Leeuwen CJ. The challenges of water, waste and climate change in cities. Environment, Development and Sustainability. 2017;19(2):385-418.
60. Kulawiak M, Lubniewski Z. SafeCity: A GIS-based tool profiled for supporting decision making in urban development and infrastructure protection. Technological Forecasting and Social Change. 2014;89:174-187.
61. Langat PK, Kumar L, Koech R. Temporal variability and trends of rainfall and streamflow in Tana River Basin, Kenya. Sustainability. 2017;9(11):1963.
62. Lawoyin JO, Nwokediegwu ZS, Gbabo EY. Client relationship management framework for trust and retention in facility services. 2020.
63. Lawoyin JO, Nwokediegwu ZS, Gbabo EY. Proposed model for integrating risk management into facility operations. 2020.

64. Leibowitz SG, Comeleo RL, Wigington PJ Jr, Weaver CP, Morefield PE, Sproles EA, *et al*. Hydrologic landscape classification evaluates streamflow vulnerability to climate change in Oregon, USA. Hydrology and Earth System Sciences. 2014;18(9):3367-3392.
65. Lemming G. Environmental assessment of contaminated site remediation in a life cycle perspective [Doctoral dissertation]. Technical University of Denmark; 2010.
66. Levy LC. Chasing fumes: The challenges posed by vapor intrusion. Nat Resources & Env't. 2013;28:20.
67. Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D. Machine learning in agriculture: A review. Sensors. 2018;18(8):2674.
68. Maas K, Schaltegger S, Crutzen N. Integrating corporate sustainability assessment, management accounting, control, and reporting. Journal of Cleaner Production. 2016;136:237-248.
69. Mark BG, Bury J, McKenzie JM, French A, Baraer M. Climate change and tropical Andean glacier recession: Evaluating hydrologic changes and livelihood vulnerability in the Cordillera Blanca, Peru. Annals of the Association of American Geographers. 2010;100(4):794-805.
70. McAlary TA, Provoost J, Dawson HE. Vapor intrusion. In: Dealing with Contaminated Sites: From Theory towards Practical Application. Dordrecht: Springer Netherlands; 2010. p. 409-453.
71. McMillan H, Montanari A, Cudennec C, Savenije H, Kreibich H, Krueger T, *et al*. Panta Rhei 2013–2015: global perspectives on hydrology, society and change. Hydrological Sciences Journal. 2016;61(7):1174-1191.
72. Meerow S, Newell JP. Spatial planning for multifunctional green infrastructure: Growing resilience in Detroit. Landscape and Urban Planning. 2017;159:62-75.
73. Mgbeahuruike LU. An investigation into soil pollution and remediation of selected polluted sites around the globe [Doctoral dissertation]. Manchester Metropolitan University; 2018.
74. Mitchell M. Long-Term Monitoring and Maintenance Plan for the Mixed Waste Landfill March 2012. No. SAND2012-1957P. Sandia National Lab. (SNL-NM), Albuquerque, NM (United States); 2012.
75. Naghibi SA, Pourghasemi HR, Dixon B. GIS-based groundwater potential mapping using boosted regression tree, classification and regression tree, and random forest machine learning models in Iran. Environmental Monitoring and Assessment. 2016;188(1):44.
76. Nashwan MS, Shahid S, Chung ES, Ahmed K, Song YH. Development of climate-based index for hydrologic hazard susceptibility. Sustainability. 2018;10(7):2182.
77. Nelitz M, Boardley S, Smith R. Tools for climate change vulnerability assessments for watersheds. Prepared by ESSA Technologies Ltd. for the Canadian Council of Ministers of the Environment; 2013.
78. Nwokediegwu ZS, Bankole AO, Okiye SE. Advancing interior and exterior construction design through large-scale 3D printing: A comprehensive review. IRE Journals. 2019;3(1):422-449. ISSN: 2456-8880.
79. Ogundipe F, Sampson E, Bakare OI, Oketola O, Folorunso A. Digital Transformation and its Role in Advancing the Sustainable Development Goals (SDGs). 2019;19:48.
80. Olatunde-Thorpe J, Aifuwa SE, Oshoba TO, Ogbuefi E. Metadata-driven access controls: Designing role-based systems for analytics teams in high-risk industries. International Journal of Multidisciplinary Research and Growth Evaluation. 2020;1(3):143-162.
81. Oni O, Adeshina YT, Iloeje KF, Olatunji OO. Artificial Intelligence Model Fairness Auditor For Loan Systems. Journal ID. 2018;8993:1162.
82. Onyekachi O, Onyeka IG, Chukwu ES, Emmanuel IO, Uzoamaka NE. Assessment of Heavy Metals; Lead (Pb), Cadmium (Cd) and Mercury (Hg) Concentration in Amaenyi Dumpsite Awka. IRE J. 2020;3:41-53.
83. Osabuohien FO. Review of the environmental impact of polymer degradation. Communication in Physical Sciences. 2017;2(1).
84. Osabuohien FO. Green Analytical Methods for Monitoring APIs and Metabolites in Nigerian Wastewater: A Pilot Environmental Risk Study. Communication In Physical Sciences. 2019;4(2):174-186.
85. Oshoba TO, Aifuwa SE, Ogbuefi E, Olatunde-Thorpe J. Portfolio Optimization with Multi-Objective Evolutionary Algorithms-Balancing Risk, Return, and Sustainability Metrics. 2020.
86. Oshoba TO, Hammed NI, Odejobi OD. Secure identity and access management model for distributed and federated systems. IRE Journals. 2019;3(4):550-567.
87. Owulade OA, Isi LR, Okereke M, Sofoluwe O, Isaac G, Olugbemi T, *et al*. Review of Reliability Engineering Techniques to Optimize Performance and Risk Management in Energy Infrastructure. Burns. 2019;18.
88. Park Y, Ligaray M, Kim YM, Kim JH, Cho KH, Sthiannopkao S. Development of enhanced groundwater arsenic prediction model using machine learning approaches in Southeast Asian countries. Desalination and Water Treatment. 2016;57(26):12227-12236.
89. Perra E, Piras M, Deidda R, Paniconi C, Mascaro G, Vivoni ER, *et al*. Multimodel assessment of climate change-induced hydrologic impacts for a Mediterranean catchment. Hydrology and Earth System Sciences. 2018;22(7):4125-4143.
90. Provoost J, Tillman F, Weaver J, Reijnders L, Bronders J, Van Keer I, *et al*. Vapour intrusion into buildings–a literature review. Soil contamination and indoor air quality. 2013;15.
91. Ransom KM, Nolan BT, Traum JA, Faunt CC, Bell AM, Gronberg JAM, *et al*. A hybrid machine learning model to predict and visualize nitrate concentration throughout the Central Valley aquifer, California, USA. Science of the Total Environment. 2017;601:1160-1172.
92. Ribeiro Neto A, Scott CA, Lima EA, Montenegro SMGL, Cirilo JA. Infrastructure sufficiency in meeting water demand under climate-induced socio-hydrological transition in the urbanizing Capibaribe River basin–Brazil. Hydrology and Earth System Sciences. 2014;18(9):3449-3459.
93. Rikalovic A, Cosic I, Lazarevic D. GIS based multi-criteria analysis for industrial site selection. Procedia Engineering. 2014;69:1054-1063.
94. Rodriguez-Galiano V, Mendes MP, Garcia-Soldado MJ, Chica-Olmo M, Ribeiro L. Predictive modeling of groundwater nitrate pollution using Random Forest and multisource variables related to intrinsic and specific vulnerability: A case study in an agricultural setting

(Southern Spain). Science of the Total Environment. 2014;476:189-206.
95. Roghani M. Investigation of Volatile Organic Compounds (VOCs) Detected at Vapor Intrusion sites. 2018.
96. Sanusi AN, Bayeroju OF, Queen Z, Nwokediegwu S. Circular Economy Integration in Construction: Conceptual Framework for Modular Housing Adoption. 2019.
97. Sayles LR. Managing large systems: organizations for the future. Routledge; 2017.
98. Schaltegger S, Csutora M. Carbon accounting for sustainability and management. Status quo and challenges. Journal of Cleaner Production. 2012;36:1-16.
99. Singh KP, Gupta S, Mohan D. Evaluating influences of seasonal variations and anthropogenic activities on alluvial groundwater hydrochemistry using ensemble learning approaches. Journal of Hydrology. 2014;511:254-266.
100. Singh R, van Werkhoven K, Wagener T. Hydrological impacts of climate change in gauged and ungauged watersheds of the Olifants basin: a trading-space-for-time approach. Hydrological Sciences Journal. 2014;59(1):29-55.
101. Steininger KW, Lininger C, Meyer LH, Muñoz P, Schinko T. Multiple carbon accounting to support just and effective climate policies. Nature Climate Change. 2016;6(1):35-41.
102. Sultani R, Soliman A, Al-Hagla K. The use of geographic information system (GIS) based spatial decision support system (SDSS) in developing the urban planning process. Architecture & Planning Journal. 2009;20:97-115.
103. Sweeney MW, Kabouris JC. Modeling, instrumentation, automation, and optimization of water resource recovery facilities. Water Environment Research. 2017;89(10):1299-1314.
104. Tang Q, Luo L. Carbon management systems and carbon mitigation. Australian Accounting Review. 2014;24(1):84-98.
105. Turczynowicz L, Pisaniello D, Williamson T. Health risk assessment and vapor intrusion: A review and Australian perspective. Human and Ecological Risk Assessment: An International Journal. 2012;18(5):984-1013.
106. Van Cauwenbergh N, Ciuró AB, Ahlers R. Participatory processes and support tools for planning in complex dynamic environments. Ecology and Society. 2018;23(2).
107. Viviroli D, Archer DR, Buytaert W, Fowler HJ, Greenwood GB, Hamlet AF, *et al*. Climate change and mountain water resources: overview and recommendations for research, management and policy. Hydrology and Earth System Sciences. 2011;15(2):471-504.
108. Wagesho N. Catchment dynamics and its impact on runoff generation: coupling watershed modelling and statistical analysis to detect catchment responses. International Journal of Water Resources and Environmental Engineering. 2014;6(2):73-87.
109. Wang H, Cai Y, Tan Q, Zeng Y. Evaluation of groundwater remediation technologies based on fuzzy multi-criteria decision analysis approaches. Water. 2017;9(6):443.
110. Wang X, Unger AJ, Parker BL. Risk-Based Characterization for Vapour Intrusion at a Conceptual Brownfields Site: Part 2. Pricing the Risk Capital. Journal of Civil Engineering. 2014;3(4):189-208.
111. Watts G, Battarbee RW, Bloomfield JP, Crossman J, Daccache A, Durance I, *et al*. Climate change and water in the UK–past changes and future prospects. Progress in Physical Geography. 2015;39(1):6-28.
112. Williamson M. Advanced simulation capability for environmental management (ASCEM): An overview of. 2011.
113. Williamson M, Meza J, Moulton D, Gorton I, Freshley M, Dixon P, *et al*. Advanced simulation capability for environmental management (ASCEM): an overview of initial results. Technology & Innovation. 2011;13(2):175-199.