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**REVIEW**

# Groundwater Vulnerability Assessment Techniques: A Comparative Review of Models and Applications

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## ABSTRACT

Assessment of groundwater vulnerability is a prerequisite tool that safeguards the subsurface water resources against mounting pressures of contamination caused by agricultural intensification, urbanization, and industrialization. The review gives a critical and elaborate comparison of some of the most popular methods of vulnerability assessment of groundwater, such as index-based methods, process-based numerical methods, statistical methods, and new methods based on machine learning. The conceptual framework that shapes the vulnerability assessment is first discussed, which shows the difference between intrinsic and specific vulnerability and the importance of key hydrogeological factors. After that, popular models are systematically divided and analyzed according to their predictive performance, data needs, computational complexity, interpretability, and scalability. It is found that index-based models continue to be important in large-scale applications as they are simple, whereas process-based models are more physically realistic in site-specific studies but demand a lot of data. Machine learning methods are highly predictive but have difficulties concerning the dependency and transparency of the data. Multi-methodological hybrid models are promising to overcome these weaknesses. The usefulness of vulnerability assessments in groundwater management has been demonstrated through the use of the tool in a variety of different hydrogeological environments, with the problems of uncertainty, data access, and model transferability remaining. This review reveals that standardized methodologies, better uncertainty quantification, and increased incorporation of advanced data sources are necessary. The future studies must target the development of dynamic, data-driven, and hybrid frameworks in order to improve the credibility and usability of groundwater vulnerability assessment.

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# 1. Introduction

Groundwater is one of the most important freshwater resources in the world, as it provides almost half of the world's population with drinking water and serves agricultural and industrial purposes [1,2]. Groundwater is the main or even the only source of water in many areas, especially the arid and semi-arid ones. Nonetheless, the increased rate of urbanization, industrialization, and agricultural intensification in the past several decades resulted in the growth of the burdens on the groundwater systems [3,4]. Fertilizers, pesticides, industrial effluents, and new sources of contaminants like pharmaceuticals and microplastics, which have been incorporated as diffuse and point-source pollutants, have contributed greatly to the degradation of groundwater. In contrast to surface water, groundwater systems do not self-purify as rapidly as surface water and have a small capacity to do so, which makes contamination of groundwater a long-term and challenging problem to address [5]. Preventive strategies have thus been core to groundwater protection, including groundwater vulnerability assessment.

The vulnerability of groundwater to contamination was defined as groundwater vulnerability to contamination by surface or near-surface sources [6]. Vulnerability assessment has, since its initial formalization in the late twentieth century, become a basic instrument of hydrogeologists, environmental managers, and policymakers. It offers a scientific foundation for determining locations that are more likely to be contaminated, thus shaping land-use planning, groundwater surveillance, and protection measures. Two main types of vulnerability are usually identified: intrinsic vulnerability, where the behavior and the nature of a specific task are taken into account, and specific vulnerability, where the natural hydrogeological attributes of an aquifer system are considered [7]. This difference highlights the complexity of groundwater ecosystems and the necessity of various methodological tools to fit various environmental situations and management goals.

Many different types of groundwater vulnerability assessment methods have been developed over the last few decades, which can be broadly divided into index-based approaches, process-based numerical models, and data-driven machine learning or statistical models. The simplest and most popular models are index-based models (DRASTIC, GOD, and SINTACS), which are relatively easy to use and implement in Geographic Information Systems (GIS) [8,9]. They are based on the weighted product of hydrogeological parameters and can be used to generate vulnerability maps, which contributes to their appeal in the context of assessing regions. But their use of expert judgment when determining the weight of the parameters creates subjectivity and can create inconsistency among applications.

Process-based models, in contrast, model groundwater flow and contaminant transport by processes based on physical equations in more detail and in a more mechanistic manner, with a more detailed account of subsurface processes [10]. Although these models have the potential to deliver high-resolution information and are especially applicable when limited geographic areas are of interest, they need large datasets, computing infrastructure, and technical knowledge, which could limit their utility in data-sparse areas. In more recent times, statistical and machine learning models (logistic regression, artificial neural networks, support vector machines, and random forests) have become more and more popular [11]. Such empirical techniques are able to statistically define convoluted nonlinear correlations among environmental factors and contamination patterns, which tend to produce a higher predictive efficiency. However, they are prone to data quality, overfitting, and poor interpretability problems.

Although models and methodologies are abundant, no consensus as to the comparative performance, suitability, and applicability under different hydrogeological and environmental conditions has yet been reached. A lot of literature available is devoted to the use of one model or a narrow comparison of a small number of methods in a particular area. Consequently, the larger knowledge base on the performance of various techniques at large scales, data access conditions, and types of contamination is still incomplete [12]. Moreover, the rapid progress in geospatial technologies, remote sensing, and artificial intelligence has also presented new possibilities to enhance vulnerability checks, but the idea of their integration into classical systems is still not thoroughly examined [13].

The proposed review article will fill such gaps by conducting a systematic and comparative review of groundwater vulnerability assessment methods, including traditional index-based methods, physically based numerical models, and new data-based methods [14]. What is new about this work is threefold. First, it provides a single conceptual framework that connects both knowledge-based and data-based approaches, which helps to better comprehend the theoretical bases and practical points of view. Second, it provides a systematic comparison of models in terms of various assessment conditions, such as data needs, computing complexity, predictive accuracy, interpretability and scalability. This multidimensional analysis allows the analysis of the strengths and limitations of models in a more balanced manner than using accuracy as the key feature of evaluation.

Third, the review highlights how emerging pieces of technology, including GIS-based multi-criteria decision analysis, remote sensing data assimilation, and hybrid machine learning frameworks, can be applied to the evaluation of the risk of groundwater vulnerability [15]. Through synthesis of recent case studies and applications in a variety of hydrogeological environments, the article identifies future trends of dynamic, data-rich, and adaptable vulnerability mapping. It also critically reviews the issues of uncertainty quantification, parameter sensitivity, and model validation that are not usually reported but are vital in assuring the reliability of vulnerability assessment.

The other role of the study that is significant is that it identified the research gaps and future directions. Specifically, this has been exacerbated by the absence of standardized methodologies and benchmarking protocols, which hamper comparability of the results across different studies. The review explains that there is a necessity for harmonization of evaluation metrics, enhanced data sharing, and the creation of hybrid solutions that will integrate the advantages of physical understanding and information-driven learning [16]. In addition to this, the growing access to high-resolution spatial and temporal information gives promise to a shift towards dynamic, rather than static, vulnerability assessments with the capacity to better represent temporal variability in recharge, land use, and contaminant loading [6].

Overall, this review aims to present a critical and overall synthesis of techniques used to assess groundwater vulnerability, which can help to understand how it has developed, what it is now, and what it will be in the future. The article will assist scholars and practitioners in choosing the right methods to use for particular goals and data circumstances by presenting an ordered comparison of models and their use in various situations. Finally, there should be a further development of the science of groundwater vulnerability assessment to improve the protection and sustainable management of this invaluable resource in the face of increasing environmental pressure and global warming.

## 2. Conceptual Framework of Groundwater Vulnerability Assessment

### 2.1. Definition and Evolution of the Vulnerability Concept

The concept of groundwater vulnerability has evolved considerably since its initial introduction in the late twentieth century, reflecting both advances in hydrogeological understanding and the growing need for effective groundwater protection strategies [17]. Early definitions framed vulnerability as the intrinsic susceptibility of groundwater to contamination, primarily governed by natural characteristics such as soil properties, depth to the water table, and aquifer permeability. This intrinsic perspective emphasized the inherent protective capacity of the subsurface environment, independent of specific contaminants or land-use practices [18].

Over time, the concept expanded to incorporate the influence of particular pollutants, giving rise to the distinction between intrinsic and specific vulnerability. Intrinsic vulnerability refers to the natural ability of the hydrogeological system to attenuate contaminants, whereas specific vulnerability accounts for the physicochemical properties of individual contaminants, such as mobility, persistence, and reactivity. This evolution reflects a shift from generalized assessments toward more context-sensitive analyses that better support risk-based management.

Despite its widespread use, the vulnerability concept remains subject to debate. One major critique is its inherent abstraction, as vulnerability does not directly measure contamination but rather the potential for it to occur. This distinction can lead to ambiguity in interpretation, particularly when vulnerability maps are used for policy decisions. Moreover, different studies often adopt varying definitions and conceptualizations, complicating comparisons across regions and methodologies. As such, there is an ongoing need to clarify and standardize the conceptual basis of groundwater vulnerability to enhance its scientific robustness and practical utility [19].

## 2.2. Hydrogeological Controls on Groundwater Vulnerability

The hydrogeology factors that determine the movement of water and contaminants through the surface to the aquifer are the fundamental determinants of groundwater vulnerability [7]. **Figure 1** is the concept diagram of these pathways and controlling factors. Of these, the nature of the unsaturated zone is essential, as this is the layer that serves as the initial obstacle to the movement of the contaminants. Organic matter content, soil texture, and soil structure affect the rate of infiltration, its adsorption capacity, and biodegradation. Highly permeable coarse-grained soils are more likely to cause rapid percolation, thus exposing the soil to more vulnerability, but fine-grained soils that have more clay content can be more effective in attenuation through adsorption and lower hydraulic conductivity.

Another important determinant is the depth of the groundwater table, since it determines the distance and time that the contaminants will travel to be attenuated [21]. Shallow water tables are normally associated with more vulnerability, as the residence period in the unsaturated zone is less. Whereas deeper aquifers can be receiving greater protection of nature, not everywhere is this true, especially in fractured or karstic systems, where preferential flow paths can circumvent protective layers.

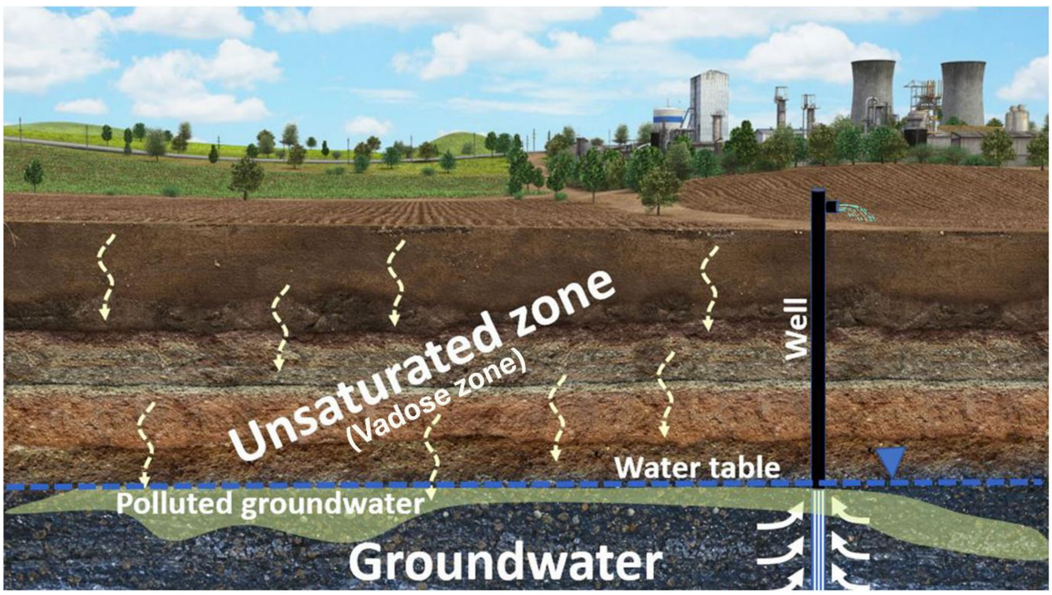


**Figure 1.** Conceptual framework of groundwater vulnerability assessment showing contaminant movement from the land surface through the soil and vadose zone to the saturated aquifer, including major controlling hydrogeological factors.

Source: Modified from the study by Dahan [20].

The vulnerability is also affected by aquifer properties such as hydraulic conductivity, porosity, and heterogeneity [22]. The aquifer properties determine the movement and dispersion of contaminants in the saturated zone. Very porous aquifers permit rapid movement of contaminants, and this could cause pollution to travel a long distance. Nevertheless, in heterogeneous mixtures, intricate flow patterns are brought in that are hard to predict and model. The recharge rates also have a dual role in that increased recharge can lead to increased dilution whereas the rate can also result in increased contaminant downward movement.

One of the most critical observations to be made in the light of recent research is the necessity of considering the interactions between these factors, and not taking them as independent variables [23]. The traditional models tend to take the form of linear relationships but the real process is very non-linear and site-specific. This complexity gives stress to the constraints of simplified conceptualizations and the need to adopt integrated approaches that have a greater representation of system dynamics.

## 2.3. Intrinsic versus Specific Vulnerability

The difference between intrinsic and specific vulnerability is another key theme of groundwater vulnerability assessment, as it is indicative of various methodological philosophies and contexts of use. Intrinsic vulnerability is concerned with inherent properties of the hydrogeological system, and it serves as a generalized evaluation of susceptibility and is independent of specific contaminants [7]. It is especially effective to map the region and conduct initial screening because the method requires quite minimal information and applies to various environments.

Intrinsic vulnerability has, however, been criticized for lacking specificity in that intrinsic vulnerability does not explain the behavior of individual contaminants [24]. An example is that a very permeable aquifer can be termed as intrinsically vulnerable, but some less mobile contaminants or adsorptive-behavior contaminants can be of limited danger in such a system. This shortcoming has prompted the development of special vulnerability tests, which have taken into consideration contaminant-specific parameters, including solubility, degradation rate, and chemical reaction with the subsurface environment.

Specific vulnerability provides a more realistic account of the contamination risk, but complicates and increases the data needs [25]. It frequently requires the detailed data of the sources of contaminants, their mechanisms of transportation, and conditions of the environment, which are not always easily accessible. Besides, the process of selecting the relevant parameters and incorporating them into assessment models may be very cumbersome, especially when performing the job with a set of contaminants with different properties.

A new vision suggests a combination of both intrinsic and specific vulnerability ideas. This method acknowledges that intrinsic factors deliver the minimum susceptibility, but there is an actual risk that is adjusted by the characteristics of contaminants and human activities [25,26]. This combined model is more in line with the principles of risk assessment and has a higher potential in informing specific management strategies.

## 2.4. Role of Data, Scale, and Uncertainty

Among the most significant preconditions of reliability and applicability of groundwater vulnerability assessments, data availability and quality should be mentioned. Historical index-based models were developed to operate with small collections of data, frequently using generalized or proxy data [7,27]. Although it is an advantage in terms of practicality, it also poses serious uncertainties, especially in areas that are under sparse monitoring networks or with varying geological natures.

Scale is the other consideration, which is basic and determines the choice of assessment methods as well as results interpretation [28]. On a regional basis, vulnerability assessments are designed to determine general trends and focus on areas that require further investigation. Simple models and coarser data resolutions could be suitable in such situations. At the local or site-specific scale, however, finer scales of analysis are necessary to reflect finer-scale variability and aid decisions. The difficulty is to match these various scales, since models created on one scale do not necessarily transfer directly to another.

Uncertainty can be generated due to a variety of sources, and these are data limitations, model assumptions, parameter estimation, and spatial variability [29]. Although important, uncertainty is usually not properly tackled in vulnerability studies, which results in overconfidence in the model outputs. Sensitivity analysis and quantification of uncertainty may give insights into the soundness of the assessments, but there is an inconsistency in using the techniques.

The latest developments in the field of geospatial technologies and data integration provide a chance to minimize uncertainty and enhance the performance of models [30]. The high-resolution remote sensing data, such as these, can improve the description of the land use, the soil characteristics, and the recharge processes. Equally, more and more groundwater quality monitoring information is becoming available, allowing more rigorous model calibration and validation. Nonetheless, all these developments also bring with them new issues on data processing, integration, and interpretation, and underscores the urgency of methodological standardization.

### 2.5. Conceptual Limitations and Emerging Perspectives

Although the engagement of groundwater vulnerability assessment has become a popular instrument, its theoretical basis and practical use are not unlimited. Among the main problems is the simplification of complex hydrogeological processes in essence [31]. Most models are based on fixed behavior of dynamic systems that do not consider any variation of factors like recharge, land use, and loading of contaminants with time. This drawback may result in the mismatch of predicted vulnerability and real patterns of contamination.

The subjectivity in the selection and weighting of parameters, especially in index-based models, is another very important concern [32]. Model inputs are also a major subject of expert judgment and may create bias and decrease reproducibility. Not all alternatives to these approaches are challenge-free, but even the use of statistical and machine learning methods can face issues such as data dependency and limited interpretability.

Moreover, the conventional emphasis on physical and chemical variables usually does not take into account socio-economic and land-use processes, which are potential contributors to the risk of contamination [6]. These factors continue to be a challenge to incorporate into the vulnerability tests but are necessary in more comprehensive and policy-oriented frameworks.

New directions in the field include the shift between mapping vulnerabilities as static to dynamic and adaptive assessments [33]. This is aided by the development of data availability, computing power, and modeling methods, which allow the addition of temporal variability and real-time monitoring. Hybrid methods, in which both physically based and data-driven methods are used, are also becoming increasingly popular and have the potential to exploit the benefits of each paradigm.

Also, the necessity to improve comparability and reproducibility through the use of standardized methodologies and benchmarking protocols is increasingly being recognized. The regional and international approaches to collaboration can be very important in terms of setting up the best practices as well as sharing data. Finally, it is necessary to discuss these conceptual and methodological issues to develop groundwater vulnerability assessment as an efficient instrument of sustainable groundwater management [34].

## 3. Overview of Groundwater Vulnerability Assessment Models

### 3.1. Classification of Vulnerability Assessment Approaches

There are three major groups of groundwater vulnerability assessment models: index-based (parametric) models, process-based (numerical) models, and data-driven (statistical and machine learning) models [33]. The general classification scheme and how these model families relate to each other are depicted in **Figure 2**. Besides this, hybrid structures that combine aspects of these groups have also been developed over the last few years. This categorization is a manifestation of the philosophy behind each technique, with expert-based simplification of hydrogeological processes on one end, and complete data predictive systems on the other end.

The index-based models are based on the hydrogeological knowledge and are founded on the integration of various environmental parameters by overlay techniques using weights. Process-based models, on the other hand, model the physical processes involved in the movement of groundwater and the movement of contaminants through mathematical formulations. Data-driven models change the emphasis to empirical relations based on observed data, usually without necessarily modeling the underlying physical processes. The categories represent all trade-offs between complexity, data need, interpretability, and predictive performance [35,36].

One of the problems with this classification is that there is no clear-cut line between categories, especially as hybrid approaches are becoming more popular. As an example, multi-criteria decision analysis (MCDA) GIS frameworks tend to include a combination of expert judgment together with statistical calibration, whereas machine learning models can be restricted or constrained by physical knowledge [37]. This convergence is a manifestation of a more general tendency towards integrative modelling, but it also increases the difficulty of an evaluation and comparison of various strategies.

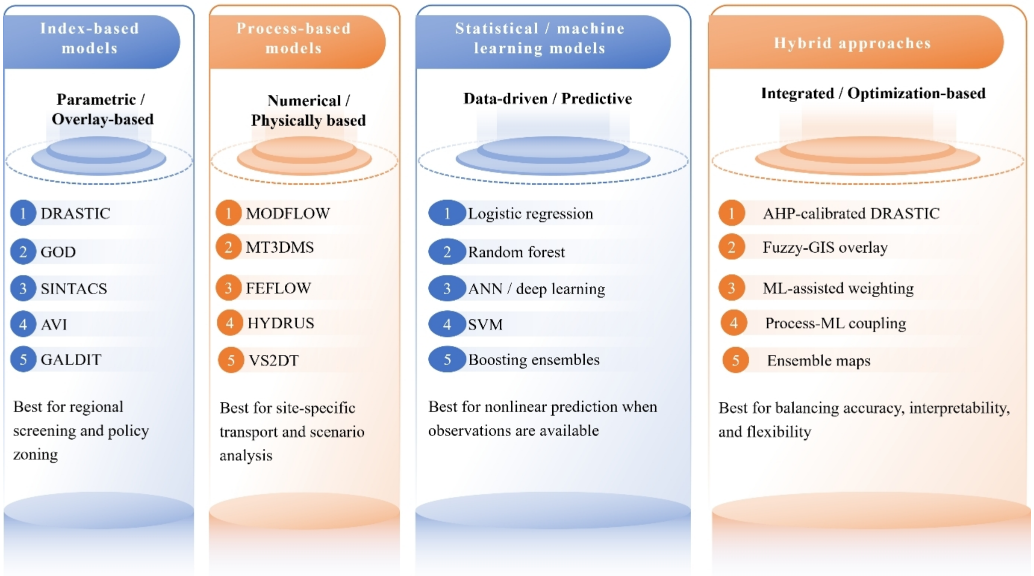


**Figure 2.** Classification of groundwater vulnerability assessment models into index-based, process-based, statistical, machine learning, and hybrid approaches.

## 3.2. Index-Based Models

Index-based models are the most popular models that are used in assessing the vulnerability of groundwater, especially at regional levels. The underlying assumption of these models is that vulnerability may be estimated by summing significant hydrogeological parameters that have a rating and a weight of their relative importance. The most notable models include DRASTIC, GOD, SINTACS, and AVI, that variously select parameters, weight, and focus on their concepts [34]. Key properties of these popular models, along with their practical merits and limitations, are summarized in **Table 1**.

**Table 1.** Major groundwater vulnerability assessment models, their principal input parameters, strengths, limitations, and typical applications.

| Model | Category | Parameters Included | Strengths | Limitations | Typical Applications |
|---|---|---|---|---|---|
| DRASTIC | Index-based | Depth, Recharge, Aquifer, Soil, Topography, Vadose zone, Conductivity | Widely used, simple, GIS-compatible | Subjective weighting, limited flexibility | Regional vulnerability mapping |
| GOD | Index-based | Groundwater occurrence, Overlying strata, Depth | Simple, minimal data requirement | Oversimplified, low resolution | Preliminary assessments |
| SINTACS | Index-based | Similar to DRASTIC with flexible weights | Adaptable to different environments | Requires calibration | Mediterranean regions |
| AVI | Index-based | Hydraulic resistance, thickness of layers | Easy implementation | Limited parameter coverage | Aquifer protection zoning |
| MOD-FLOW/MT3DMS | Process-based | Flow and transport parameters | High physical realism | Data-intensive, computationally complex | Site-specific studies |

An example is the DRASTIC model, which has seven parameters such as depth to water, net recharge, aquifer media, soil media, topography, effects of the vadose zone, and hydraulic conductivity [38]. These parameters are given a standardized weight and rating, which is summed to generate an index of vulnerability. Likewise, the GOD model eases the evaluation through paying attention to the occurrence of groundwater, the strata above, and groundwater depth, whereas SINTACS adjusts the DRASTIC model to the Mediterranean context by allowing the schemes of weighting to be flexible [39,40].

The main benefit associated with index-based models is that they are simple, transparent, and easy to implement in a GIS setup [41]. They do not have a high data requirement and can be used across extensive spatial scales, which is especially useful when preliminary assessments are necessary and decision support is needed. These strengths, however, come with significant drawbacks. Fixed or semi-empirical weighting schemes are subjective, and the fact that the relationships between the different parameters are assumed to be linear can oversimplify complicated hydrogeological processes.

Also, index-based models are not always sensitive to local conditions and can be insufficient to describe the effects of preferential flow paths, heterogeneity, or temporal variability [42]. Attempts to develop these models have involved sensitivity analysis, weight optimization, and the use of fuzzy logic to capture uncertainty better. Though these developments were made, it is still impossible to address the fundamental dilemma of simplicity and realism.

### 3.3. Process-Based Models

Process-based models represent an entirely different method since they explicitly model the processes of groundwater flow and transport of the contaminant using the physical governing equations [31]. They are models that are commonly performed using software (e.g., MODFLOW and MT3DMS) and which are founded on the concepts of fluid dynamics and mass transport, permitting an in-depth depiction of the circumstances in the underground [43].

Among the main advantages of the process-based models, the fact that they can help to consider the spatial and temporal heterogeneity, which can be explained by the temporary flow conditions, variable recharge, and complicated interactions of boundaries, must be listed [31]. This is what renders them highly useful to site-specific evaluation, evaluation of contamination risk, and to test scenarios. As an illustration, they have the ability to model how the pollutants move in response to varying land-use or climate change conditions, which gives an insight into future vulnerability.

The use of process-based models is, however, limited by the high data and calculation demands. Proper model development requires a great deal of information about hydrogeological characteristics, boundary conditions, and characteristics of contaminants, and such information may not be readily available in most areas [44]. The process of calibration and validation is also a resource that is resource consuming and may create extra uncertainty in the case of limited or unreliable observational data.

Scalability is another important limitation [45]. Although process-based models are effective at the local or site-specific scales, they are not applicable at scales of region or nations because of computational limitations and the heterogeneity of data. Moreover, the sophistication of such models may reduce their usability and understandability, especially at a level not related to the scientific community. They are therefore not used extensively in their normal vulnerability mapping and policy making.

### 3.4. Statistical and Machine Learning Approaches

Owing to the rising availability of environmental data and the development of computational techniques, the use of statistical and machine learning in the field of groundwater vulnerability assessment has become increasingly popular [33]. These approaches seek to determine empirical correlations of environmental variables and measured indicators of contamination, e. g., nitrate levels, but do not explicitly model the physical processes.

Conventional statistical techniques like the logistic regression and multivariate analysis give a comparatively clear system of evaluating the impact of various variables on groundwater pollution [46]. They enable the test of hypotheses and estimation of the significance of parameters and provide information on the relative importance of different predictors. Nonlinear interactions are, however, limited in their capability to capture them.

Artificial neural networks, decision trees, random forests, and support vector machines are all machine learning methods that have proven to have significant potential in overcoming these shortcomings [47]. These models are capable of dealing with large amounts of data, handling nonlinear relations, and have high predictive accuracy. Machine learning methods have, in most case studies, performed better compared with traditional index-based models, especially in situations where a large amount of training data is at hand.

Regardless of these benefits, there is no problem with data-driven approaches. The quality of the quantity and representativeness of the input data can be of great importance to their performance. They can be very limited in application in data-scarce areas. Also, most machine learning models are frequently condemned as black boxes, with the inner mechanics of such models not always being easy to understand. This transparency may lessen confidence to the decision-makers and impede its implementation in the regulatory fields [16].

Recent trends in explainable AI (XAI) seek to solve this problem by offering the means to interpret the results of a model and interpret variable significance [48,49]. However, the balance between predictive performance and interpretability is one of the main issues in machine learning applications to assess the vulnerability of groundwater.

### 3.5. Hybrid and GIS-Based Approaches

The need to address the shortcomings of each modeling method has led to the appearance of hybrid methods that seek to incorporate the best of each approach and reduce the worst. The methods are frequently a combination of index-based approaches with statistical or machine learning, or GIS-based spatial analysis applications [50].

GIS has been at the center of contemporary vulnerability assessment as it allows the use of spatial data to integrate, visualize, and analyze them [51]. Multi-criteria decision analysis (MCDA) methods like the analytic hierarchy process (AHP) are widely applied to obtain weights on parameters in index-based models, eliminating subjectivity by making decisions systematically. These weights are further optimized with statistical or machine learning methods in certain cases, producing more resilient and more informed models.

Hybrid models can also be associated with process-based simulation and data-driven simulation [52]. An example is that a machine learning algorithm can take the output of a numerical model as an input to increase the predictive power, whilst maintaining some physical realism. On the other hand, complex physical processes can be approximated with machine learning models, eliminating the need to do this computationally.

Although hybrid approaches have the potential to be very effective, it also brings new complexities of integrating the model, compatibility of parameters, and validation [14]. This mix of other methodologies may blur the hidden assumptions and elevate the chances of overfitting or multiplicity. Thus, to guarantee the reliability and transparency of hybrid models, the design needs to be thoroughly done, and their evaluation needs to be carefully conducted.

### 3.6. Critical Synthesis and Model Selection Considerations

The variety of the groundwater vulnerability assessment models is indicative of the complex nature of the concern, but it also makes it difficult to select and compare models. There is no universal best method because the appropriateness of a model varies depending on the purpose, data available, the scale of space, and the hydrogeological settings.

Index-based models have the benefit of making a quick and large-scale assessment, and also in situations where the data are scarce [41]. Process-based models have offered site-level information despite their complexity and resource needs [53]. Data-driven methods are highly predictive in nature, but they require the availability of data, and they might not be interpretable [54]. Hybrid models are a potentially effective way of going, but need special attention so as not to add to uncertainties [55]. One important lesson to be learned is that the purpose of assessment and associated trade-offs must guide the model selection. Instead of trying to find just one best model, it might be more fitting to take the multi-model approach, where other methods are applied complementary to each other. This would be capable of strengthening and offering a more detailed view of the vulnerability of groundwater.

To sum up, the changing face of vulnerability assessment models represents an opportunity where further methodological innovation and integration are required [33]. Future studies must aim at enhancing model comparability, better data integration, and coming up with frameworks that are balanced in terms of accuracy, interpretability, and practicality. These developments are mandatory to make the vulnerability assessment an effective instrument of groundwater protection in a more sophisticated yet more information-saturated world.

## 4. Comparative Analysis of Groundwater Vulnerability Assessment Models

### 4.1. Evaluation Criteria and Comparative Framework

The successful comparison of groundwater vulnerability assessment models would involve the need to have a standardized evaluation framework that takes into consideration both technical performance and practical applicability [56]. Historically, model comparison has emphasized predictive accuracy, which is usually measured by correlation with observed contamination indicators like nitrate concentrations. Nevertheless, this tunnel vision does not recognize other important dimensions such as data demands, complexity of computation, interpretability, scaling, and the ability to perform under different hydrogeological conditions.

An even more detailed assessment system should thus take a multi-criteria approach. The synthesized **Table 2** presents these comparative dimensions and their overall implications for the major model families. The importance of accuracy should still be taken into consideration, which is coupled with the notions of reliability and reproducibility. Another important aspect is data dependency, because the models that can be successfully used in data-rich areas might not be effective in areas with scarce data. Computational efficiency and ease of implementation determine the possibility of applying models in the routine management setting. Interpretability applies especially in the field of policy-making and decision-making, which require explainable and clear outputs [16].

In addition, the weighting of these criteria should be determined by the nature of the assessment, i.e., the purpose of the assessment is screening, detailed analysis, or predictive modeling. As an example, planning at a regional scale can value simplicity and scalability, and site-specific risk assessment can require greater accuracy and physical realism [57]. Such a contextual dependency underscores the need to integrate model choice and management goals as opposed to using generic performance measures.

**Table 2.** Comparative evaluation of major groundwater vulnerability model types based on predictive performance, data demand, computational complexity, interpretability, scalability, and flexibility.

| Criteria | Index-Based Models | Process-Based Models | Machine Learning Models | Hybrid Models |
|---|---|---|---|---|
| Predictive Accuracy | Moderate | High | High | Very high (potential) |
| Data Requirement | Low | Very high | High | Moderate–High |
| Computational Demand | Low | Very high | Moderate–High | High |
| Interpretability | High | Moderate | Low (black-box) | Moderate |
| Scalability | High | Low | Moderate | Moderate–High |
| Flexibility | Low | Moderate | High | High |

## 4.2. Accuracy and Predictive Performance

Predictive performance is considered to be the main one used to evaluate the vulnerability models; however, it is quite challenging to measure because vulnerability, as a concept, is indirect [56]. Because vulnerability is a conceptual (not a quantifiable) attribute, its validation is usually achieved using proxy measures (groundwater contamination data). Of these, the most popular ones are nitrate concentrations because they are the most widespread and relatively conservative in a groundwater system.

Index-based models typically have a moderate predictive power, particularly in homogeneous regions where the underlying assumptions are reasonably good [58]. They may, however, be greatly affected by the choice of parameters and weighting schemes affecting performance. The predictive accuracy has been improved in most cases by local calibration or combining it with statistical methods, which is an indication that the original standardized formulations might not be widely applicable.

Process-based models, in their turn, provide a greater potential accuracy because of their clear physical representation [59]. They can be used to make detailed predictions of the contaminant transport when they are properly calibrated, and the data is of high quality. However, they are very sensitive to input information and boundary conditions, and any inaccuracies in these inputs may be propagated through the model, which may compromise accuracy.

Machine learning systems are more predictive, especially in nonlinear and heterogeneous environments that have complex relationships [60]. It has been demonstrated that machine algorithms like neural networks and random forests can be more accurate in classification and are able to predict. Yet this generalization should be taken with reserve because what is highly accurate on training or validation sets does not always mean that it will be accurate in other regions or in other time frames. Overfitting and data bias are still of great concern.

### 4.3. Data Requirements and Practical Applicability

The availability of data is one of the most essential limitations of groundwater vulnerability assessment and a decisive factor in explaining the appropriateness of various models [45]. The index-based models are only meant to work with relatively small datasets, and their parameters are usually easy to access or even inferred, like the soil type, land use, and topography. This renders them especially appealing to developing areas or to extensive research through which the finer hydrogeological information is not readily available.

Process-based models, on the other hand, demand large and detailed data in the form of hydraulic characteristics, boundary conditions, and time-varying recharge and contaminant sources [61]. Processing and acquisition of this data can be resource-intensive, and these models will only be useful in well-studied regions or in individual projects that have adequate financial means and technical knowledge.

Machine learning solutions have a middle ground regarding the data needs [62]. They do not need explicit information about physical processes, but they are highly reliant on the accessibility of large and representative datasets to train and validate them. In sparsely or biased data, they can be rendered inefficient in those areas. In addition, the blending of heterogeneous sources of data, including remote sensing and in-situ measurements, brings along with them new issues associated with balancing data and quality management.

In practical terms, a trade-off between the data needs and the model performance is a key consideration [62]. Less complex models can be more accurate and applicable, whereas more complex models can be detailed at the expense of being less transferable. The given trade-off helps to emphasize the significance of a context-dependent choice of models and the necessity to have a flexible framework that could be adapted to different data conditions.

### 4.4. Interpretability and Decision-Making Relevance

The adoptability of the vulnerability assessment models is determined mainly by interpretability as a factor. The stakeholders would find it easier to accept and implement models that yield transparent and easily understandable results in the decision-making processes [63]. In this respect, index-based models possess an undoubted advantage, being comparatively easier in their structure and outputs and relating directly to physical parameters.

The process-based models, being based on physical principles, may be harder to interpret, as they are complex, with a large number of interacting variables being large. Their products are frequently too technical to be easily read by ordinary audiences and might not be communicated easily to non-expert groups. However, they can better fit into the purposeful use by their ability to model a particular situation and present information in more detail [64].

The hardest challenge in terms of interpretability is machine learning models [65]. Lots of algorithms are black boxes, which make predictions without an apparent description of the underlying relationships. Such absence of transparency may limit its acceptance, especially where accountability and justification are critical aspects, such as in the regulatory environment. Recent explainable AI advances, including feature importance analysis and model-agnostic interpretation methods, have started to solve this problem, but have not been widely applied to groundwater research.

An important point is that interpretability is not to be regarded as a characteristic of a model, but a factor of the implementation and communication of the model [66]. It might be promising that using hybrid methods to create a combination of data-driven predictions and physically meaningful variables provides a way into the future in terms of the balance between accuracy and interpretability.

### 4.5. Sensitivity, Uncertainty, and Robustness

All groundwater vulnerability assessments are invariably subject to some degree of uncertainty due to the constraints of available data and model assumptions, as well as natural variability [29]. Sensitivity analysis gives an opportunity to determine the most important parameters and the stability of the model outputs in different circumstances. Sensitivity analysis has indicated in index-based models that the weighting of parameters can be very important, and therefore, great care should be taken to calibrate and validate.

Process-based models are vulnerable to uncertainty in terms of parameter estimation, boundary conditions, and model structure [67]. Although deep approaches like stochastic modeling and Monte Carlo simulations are applicable in the quantification of uncertainty, they are usually constrained due to computational limitations. In addition, interpretation of the uncertainty outputs needs a high level of expertise that will not always be present.

The machine learning models are associated with new sources of uncertainty because of data quality, model selection, and training procedures [68]. Although ensemble methods and cross-validation methods may enhance robustness, they are not able to entirely remove the possibility of overfitting or bias. Also, there may be no clear physical representation, which can complicate the task of evaluating how plausible model results are.

One major problem with all types of models is the minimal focus on uncertainty communication [55]. Vulnerability maps are typically shown as non-probabilistic results, without very much detail about the degree of uncertainty or possible errors. This may be misconstrued and lead to inappropriate decision-making. It is thus important to increase the credibility and utility of vulnerability assessments by increasing the transparency and communication of uncertainty.

### 4.6. Transferability and Scalability

The usefulness of a model is a point of much importance in its ability to be applicable in various spatial and environmental settings [41]. The models based on indices tend to be more transferable since they are standardized, and they use more common parameters. Their application to areas with very different hydrogeological conditions, however, can lead to poor performance, requiring a local calibration or adaptation.

Process-based models, though very precise on a local scale, can be hard to extrapolate because they rely on local site data and conditions [31]. The extension of such models to bigger areas brings up considerable difficulties pertaining to data heterogeneity and computer resources. Consequently, they are usually limited in scope to localized studies. The machine learning models have mixed transferability. Although they are able to find complicated patterns within a specific set of data, their effectiveness might decrease when they are utilized in other areas that have various features. This is especially severe when the training information is not reflective of the target environment. In its current form, the transfer learning and domain adaptation methods provide some solutions, yet their use in the context of groundwater research remains in an infantile phase.

Scalability is the nearest concept to transferability, but it is concerned with the capability to scale to a greater spatial extent or greater data volume [28]. The versatility of most models, especially index-based and data-driven models, has been improved with the GIS-based framework and cloud computing technologies. However, the ability to deliver uniform performance across scales is still a great challenge.

### 4.7. Synthesis and Implications for Model Selection

The actual comparison of the groundwater vulnerability assessment models has shown that each of these models has its own strengths and weaknesses, and none of the models is applicable in all cases and outperforms the others in all cases. **Table 3** summarises these trade-offs and the consequences of these trade-offs on the selection of practical models. Index-based models are easy to use and have wide applicability, but they might not be accurate and flexible [41]. Process-based models provide physically justified and detailed information but have data and computational requirements [31]. Machine learning methods are highly predictive but have difficulties with interpretability and data dependency [69].

**Table 3.** Advantages, principal limitations, and recommended application contexts of index-based, process-based, machine learning, and hybrid groundwater vulnerability models.

| Model Type | Advantages | Main Limitations | Recommended Use Cases |
|---|---|---|---|
| Index-Based | Simple, low data needs, easy GIS integration | Subjectivity, limited physical realism | Regional screening, policy support |
| Process-Based | Physically accurate, scenario simulation | Data- and computation-intensive | Site-specific risk assessment |
| Machine Learning | High predictive performance, nonlinear modeling | Requires large datasets, low interpretability | Data-rich regions, prediction tasks |
| Hybrid Models | Combines strengths of multiple approaches | Complex implementation, validation issues | Advanced integrated assessments |

The implications of this analysis include that the selection of the model to use should be informed by a clear understanding of the assessment goals, availability of data, and spatial scale. Instead of trying to have a universal answer, practitioners need to think about using a multi-model or a complementary approach, whereby the strengths of various methods can be exploited to have a more holistic and effective assessment [70].

Further on, standardized assessment procedures and benchmarking datasets should be used to enable more consistent and transparent comparisons between models [34]. This would not only enhance the scientific rigor of the vulnerability assessments but it would also make them more practical in groundwater management.

To sum up, to move the comparative analysis of the models of vulnerability, there must be a transition to unified frameworks that would compromise accuracy, interpretability, and practicality. Through methodological diversity and interdisciplinary cooperation, the discipline can advance towards a more trustworthy and practical evaluation that would help in the protection of groundwater in a sustainable approach.

# 5. Applications and Case Studies of Groundwater Vulnerability Assessment

## 5.1. Regional and Global Applications

Models of groundwater vulnerability assessment have been extensively used in a wide variety of hydrogeological and climatic environments, including humid temperate and arid and semi-arid environments [19]. **Figure 3a** below maps the co-occurrence of water scarcity and climate sensitivity across prefectures in China, with the highlights providing areas of intense stress by water scarcity and climate sensitivity to change. **Figure 3b** shows how water scarcity and climate sensitivity are distributed in space in various prefectures in China. It defines vulnerable hotspot areas in which high water scarcity and high susceptibility to climate change co-occur, which makes these areas especially vulnerable to risks associated with water under changing climate conditions.

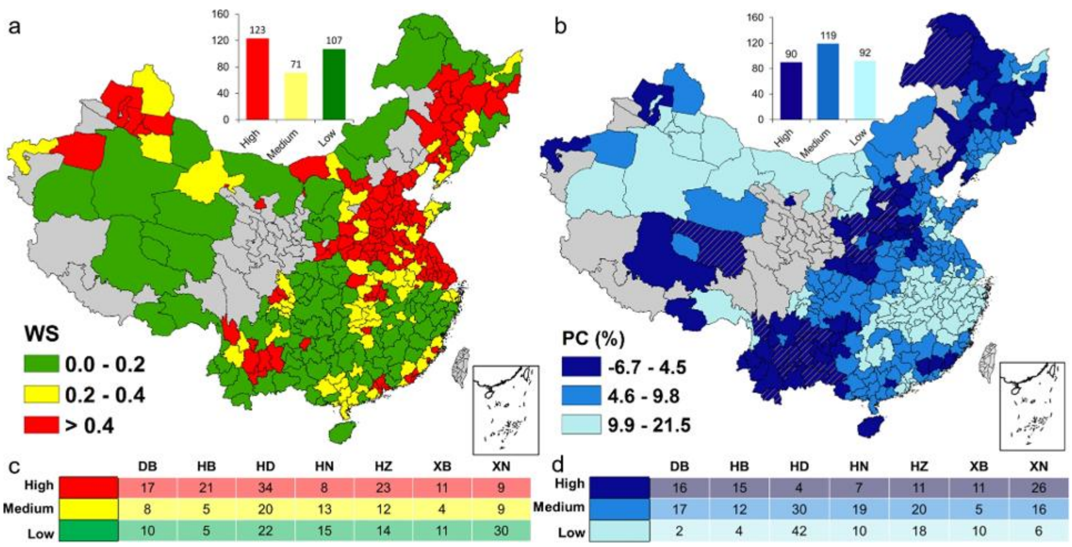


**Figure 3.** (**a**) Co-occurrence of Water Scarcity; (**b**) Climate Sensitivity at the Prefecture Level [71].

The figure represents the spatial distribution of the water scarcity (WS) and the sensitivity to climate change (PC) caused by precipitation at the prefecture level in China. Vulnerable hotspots are prefectures where water scarcity is high, and the sensitivity is high. These locations majorly fall under the Huabie (HB), Huadong (HD), Dongbei (DB), Xinan (XN), Huazhong (HZ), and Xibie (XB) districts, which are areas that have the worst risks associated with them given water scarcity as well as climate change. The number shows why there is a necessity for resourceful water management in such critical areas [71].

At the regional level, index-based models like DRASTIC and SINTACS have been widely applied in coming up with vulnerability maps, which are used in land-use planning and groundwater protection policies [72]. These applications have shown that vulnerability assessments can be of value in determining the high-risk areas, especially in agricultural areas where there are cases of diffuse pollution due to fertilizers and pesticides.

Vulnerability assessments have frequently been incorporated into wider environmental management models in developed areas where the amount of data is relatively large. As an example, vulnerability maps are regularly applied in parts of Europe and North America to map out protection areas around drinking water sources and offer direction at the regulatory levels. Conversely, in the developing world, these models have been used in a more discovery-based fashion, where data and institutional capacity have limited their usage. However, even the simplified forms have been effective in the creation of awareness and preliminary management decisions [73].

On the international level, there have been attempts to create generalized vulnerability maps, where harmonized data sets and consistent methodologies are used [21]. Although these efforts are a good general description of groundwater vulnerability, their solution and precision are limited by the roughness of accessible data. In addition, the fact that heterogeneity of hydrogeological conditions differs among regions presents considerable problems to global standardization. Consequently, global evaluations can be regarded as screening devices but hardly as sure images of local susceptibility.

The most notable point that can be made based on regional and global experience is excessive dependence on the local context, which affects model performance [70]. Something that works in one area might not give the same results in another area, and therefore, it is important to calibrate and validate the model. This reiterates the importance of locally adapting methodologies, as opposed to the direct transfer of methodologies.

### 5.2. Pollution-Specific Vulnerability Assessments

Although intrinsic vulnerability tests give a rough estimate of susceptibility, some studies have placed emphasis on individual contaminants in order to reflect the real threat to the quality of groundwater. Of all these, most concern has been given to nitrate contamination because of its prevalence and close relation to agricultural practices. Combinations of vulnerability models and nitrate concentration data are effective in several case studies that investigate and optimize model products [74].

Besides nitrates, vulnerability reviews have been carried out on a variety of other pollutants, such as pesticides, heavy metals, hydrocarbons, and emerging pollutants like pharmaceuticals and personal care products [75]. **Table 4** summarizes, comparatively, these groups of contaminants, their hydrogeochemical behavior, and evaluation techniques typically applied to these contaminants. These tests frequently involve the use of parameters that are specific to a contaminant, including degradation rates, adsorption coefficients, and transport mechanisms. Consequently, they have more of a tendency to use more process-based or hybrid models.

**Table 4.** Common groundwater contaminants, their major sources and subsurface behavior, preferred vulnerability assessment approaches, and key analytical challenges.

| Contaminant Type | Sources | Behavior in Groundwater | Preferred Assessment Methods | Challenges |
|---|---|---|---|---|
| Nitrate | Agriculture (fertilizers) | Highly mobile, persistent | Index + statistical validation | Temporal variability |
| Pesticides | Agricultural activities | Variable mobility and degradation | Process-based/hybrid models | Complex chemical behavior |
| Heavy metals | Industrial discharge | Low mobility, adsorption | Process-based models | Site-specific variability |
| Hydrocarbons | Petroleum spills | Limited solubility, slow movement | Numerical models | Heterogeneity of subsurface |
| Emerging contaminants | Pharmaceuticals, microplastics | Poorly understood behavior | Machine learning/hybrid | Data scarcity |

One of the difficulties in pollution-specific measurement is that the behavior of the contaminant varies in various conditions of the environment. Indicatively, the mobility of pesticides in the soil and their persistence can change based on the properties of soil, climate, and farming procedures [76]. Likewise, emerging contaminants have a poor understanding of their behavior, making them difficult to include in vulnerability frameworks.

Notwithstanding such issues, pollution-specific measurements do provide useful information about the relationship between human-made activities and groundwater systems [77]. They allow more specific management tactics, including the identification of the areas of the most critical sources and the priority given to mitigation measures. The additional complexity and data demands of these assessments, however, might prevent their use, especially in data-sparse areas.

## 5.3. Integration with Groundwater Management and Policy

The effective management and policy-making is one of the major objectives of groundwater vulnerability assessment [78]. Practically, vulnerable maps tend to be utilized as decision support systems to direct land-use planning, control potentially polluting activities, and design monitoring programs. As an example, the territory of high vulnerability can be restricted in terms of industrialization, agricultural inputs, or waste disposal.

Vulnerability assessment has become a part of groundwater protection regulation in a wide range of countries [19]. Wellhead protection areas and aquifer protection zones are frequently determined by vulnerability mapping with the input of hydrogeological and socio-economic reasoning. These programs reveal the pragmatic usefulness of vulnerability assessment and how it could be used to make policy-related decisions.

But there are no problems with the translation of scientific evaluation into policy. The uncertainty and limitations are one of the key problems, as the validity and the uptake of vulnerability maps may be compromised by the communication of uncertainty and limitations. Policymakers might need straightforward and practical information, but vulnerability assessments are usually full of assumptions and uncertainties [73]. To seal this gap, it is necessary to improve the methodology, but also to provide effective communication strategies.

The other challenge is integrating vulnerability assessment with the other decision-making tools, like risk assessment and cost-benefit analysis [79]. Vulnerability does not directly consider the sources of contaminants or exposure routes, although it gives information on susceptibility. It, therefore, cannot be viewed as a tool on its own.

## 5.4. Advances in Technology and Data Integration

The recent technological advancements have tremendously improved the possibilities of groundwater vulnerability assessment. GIS is no longer seen as an additional tool in spatial analysis and visualization, and it allows the combination of various datasets to create high-resolution vulnerability maps [30]. The use of remote sensing information has also increased the scope of data available, especially in areas where measurements are not available on the ground.

The remote sensing technologies offer significant information about the land use, vegetative cover, soil moisture, and surface temperature that can be applied to deduce the recharge trends and the likelihood of contamination [80,81]. These datasets can be used to enhance the precision and spatiality of vulnerability assessments when used together with traditional hydrogeological data. In addition, with growing accessibility to satellite data, it has been easy to conduct large-scale and even near-real-time monitoring of the environmental conditions.

The advent of big data and new and improved methods of calculation has provided additional avenues of vulnerability assessment [82]. Machine learning algorithms have the ability to crunch large and complicated data, which then reveal patterns and relationships that might not be easily discerned using traditional techniques. Cloud computing systems can be used to process large data sets and run an operationally intensive model, which increases their scalability and availability. Although these have been developed, issues concerning data integration and quality control are still there. Heterogeneous datasets should be preprocessed and validated with care to guarantee consistency and reliability. Also, the growing use of automated and data-driven practices raises issues of transparency and reproducibility. These are necessary concerns to ensure that vulnerability assessments are scientifically sound.

### 5.5. Challenges in Practical Implementation

Practical applications of groundwater vulnerability assessment models are usually limited by various technical, institutional, and socio-economic considerations. The scarcity of data is one of the greatest problems, especially in developing regions where networks are few and the hydrogeological information is not complete [45]. The use of complex models in such situations may not be practical, hence the use of simplified methods that can compromise on accuracy.

Another typical problem is scale mismatch because available data may not be of the required resolution to support the model selected [67]. To mention a few, regional-scale tests can be based on crudely recorded data that masks small regions, whereas location-level studies might not record enough detail to reflect fine-scale dynamics. The solution to this gap lies in the creation of multi-scale frameworks that are capable of intertwining data and models on various levels of resolution.

The institutional and policy-related issues also contribute greatly [83]. Vulnerability assessments frequently involve various stakeholders such as government agencies, researchers, and local communities, which involves coordination of the implementation process. The variation in priorities, resources, and technical capacity may act as a barrier to the adoption and proper utilization of vulnerability models. Moreover, the absence of standardized methodologies and guidelines may also cause discrepancies and lower the comparability among studies. The efficacy of vulnerability-based approaches to managing land-use is also affected by socio-economic issues, including land-use practice, economic motivation, and awareness of people and their knowledge. The effect of quality assessments can also be constrained in situations where they are not properly incorporated into decision-making or where the stakeholders are unable to take the suggested actions.

### 5.6. Emerging Trends and Future Application Directions

There is a shift in the field of groundwater vulnerability assessment to increasingly dynamic, data-driven, and integrated methods. Among the most notable tendencies is the transition to dynamic assessment of vulnerability instead of the traditional fixed vulnerability mapping in the face of temporal changeability in the environmental conditions and human activity [6]. Such a change is made possible by the developments in monitoring technologies and the availability of data, and it is possible to create the models that will be able to refresh the vulnerability estimates in near real-time.

The other trend that is on the rise is the growing application of hybrid models, which apply physical, statistical, and machine learning [84]. The idea behind these models is to utilize the strengths of the various methodologies in a way that will enhance the predictive performance, but at a certain level of interpretability. Assessment of vulnerability at a socio-economic level is also increasingly finding interest, as is a wider acknowledgment that such an approach requires the use of holistic and interdisciplinary methods. Moreover, interest is increasing in the use of vulnerability assessments for new issues, including climate change and the proliferation of new contaminants. The effect of climate change is likely to change the recharge regimes, groundwater table, and contamination pathways, and the new approach to assessment must be developed [85]. Equally, new methodologies and data are needed to efficiently determine the effect of emerging contaminants on groundwater systems as they continue to rise.

As future projections, the further evolution of the groundwater vulnerability assessment will rely on the incorporation of new technologies, better data exchange, and the creation of standardized approaches. Cooperation between fields and states will be needed in order to tackle the complicated and dynamic issues related to groundwater protection. Finally, successful vulnerability assessment implementation will be critical to the sustainable management of the groundwater resources in the context of increased environmental stress.

## 6. Conclusion

The assessment of groundwater vulnerability has turned out to be a critical part of contemporary hydrogeological studies and environmental health due to the growing pressure on the availability of groundwater resources and the necessity to develop proactive strategies for their protection. The review has given a detailed review of the conceptual underpinning, developments in methodology, performance relative to each other, and practical uses of key vulnerability assessment methods. Through a critical analysis of index-based, process-based, data-driven, and hybrid models, the study brings out the gains made and the challenges that still abound in this developing area.

One of the main conclusions made in the result of this review is that no universal modeling method can be defined as the most optimal. Index-based models are still useful in screening and decision support at a large scale because they are simple, transparent, and require minimal data. Nevertheless, they could be too dependent on generalized assumptions and subjective weighting systems, which can restrict their precision and flexibility. Models based upon processes provide a comprehensive and physically based understanding of contaminant transport processes, but are limited by the high data requirements, computational load, and scale. Machine learning and data-driven methods have proven to be highly predictive, especially in a heterogeneous environment, but require data quality and interpretability concerns are a major challenge. Combination methods, including adopting aspects of more than one methodology, are one of the future paths, but should be designed and proven to be robust and transparent. The next lesson is that context is vital in the issue of model suitability. The success of any vulnerability assessment methodology varies according to the availability of data, spatial scale, hydrogeological factors, and objectives of the study. As a result, perceived performance should not be used to select models, but rather it should be a balanced view of these factors. Probably in most instances, a multi-model or complementary methodology can give more dependable and thorough results than a single methodology.

Another point that the review highlights is that uncertainty needs to be addressed, and a better model validation is required. Even with improved methodology, there is uncertainty that is not a rare occurrence, and which is usually underestimated in vulnerability assessment. To improve the credibility and applicability of model outputs, it is necessary to improve the sensitivity analysis, probabilistic techniques, and uncertainty communication. Likewise, the creation of standardized evaluation measures and benchmarking datasets would help the comparisons to be more consistent across the studies and enhance the overall rigor levels of the field. Regarding applications, the groundwater vulnerability assessment has proven to be highly useful in informing the land-use planning, pollution control, and even groundwater protection policies. Their effectiveness, however, is usually determined by how well they have been incorporated into the decision-making processes. The gap between scientific evaluation and policy actions needs not only methodological enhancement but also more effective stakeholder involvement, effective reporting of findings, and inclusion of socio-economic factors in the assessment systems.

In the future, a number of new trends are expected to influence the future of groundwater vulnerability assessment. With the growing availability of high-resolution spatial and temporal data, along with developments in remote sensing, GIS, and computational methods, more dynamic and data-intensive measurements are becoming possible. A combination of machine learning and physically based models has provided new possibilities for enhancing predictive performance without losing interpretability. Moreover, the increased awareness of the effects of climate change and the emergence of new pollutants also outline the necessity of adaptive and proactive evaluation strategies. However, there are still serious gaps in research. These are the necessities of more methodological standardization, more integration of multi-source data, better management of uncertainty, and the creation of scalable models that can be used at various spatial and temporal ranges. To overcome these problems, it will be necessary to combine interdisciplinary efforts and combine hydrogeological, data science, environmental engineering, and policy studies knowledge.

Three primary scientific insights emerge from this comparative review. First, no single model universally outperforms others; instead, each model family embeds inherent trade-offs among accuracy, data demand, interpretability, and scalability. Second, the widespread pursuit of higher predictive accuracy—particularly via machine learning—often comes at the cost of physical transparency and transferability, challenging regulatory uptake. Third, uncertainty remains systematically under-reported and under-communicated, yet it fundamentally limits the operational reliability of vulnerability maps. For practical applications, regional screening in data-scarce settings can defensibly rely on index-based models such as DRASTIC with local sensitivity adjustment, whereas site-specific risk assessment should prioritize process-based models when adequate hydrogeological data exist. In data-rich regions, machine learning models can enhance predictive performance but must be paired with explainable AI techniques to support decision-making, and hybrid models are promising for integrated assessments provided they undergo rigorous validation to avoid compounded uncertainties. Looking forward, a phased research roadmap is needed: in the short term, the community should establish standardized benchmarking datasets and validation metrics to enable fair cross-model comparisons; in the medium term, dynamic vulnerability frameworks that incorporate temporal variability in recharge, land use, and contaminant loading should replace static maps; and in the long term, scalable, hybrid, interpretable models that couple process-based understanding with data-driven learning must be developed, supported by operational uncertainty quantification and visualization tools for end-users. Advancing groundwater vulnerability assessment along this roadmap is essential to transform it from a retrospective mapping exercise into a proactive, adaptive, and policy-relevant tool for groundwater protection under increasing environmental pressure and climate change.

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