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ASSESSMENT OF GROUNDWATER VULNERABILITY FOR SUSTAINABLE WATER RESOURCE MANAGEMENT IN SOUTHEAST HUNGARY: A COMPARATIVE ANALYSIS OF METHODOLOGICAL APPROACHES

Ph.D. Thesis

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Table of Contents

List of Abbreviations

DRASTIC	Depth to water table; Recharge rate; Aquifer media; Soil media; Topography; Impact of vadose zone; Conductivity (hydraulic)
FIS	Fuzzy Inference Systems
FL	Fuzzy Logic
GIS	Geographic Information System
GOD	Groundwater occurrence; Overlying lithology; Depth of water table
GPS	Global Positioning System
H	High
L	Low
LU/LC	Land Use/Land Cover
M	Moderate
mbgl	Meter Below Ground Level
MF	Membership Function
SI	Susceptibility Index
SPSA	Single-Parameter Sensitivity Analysis
SPSS	Statistical Package for the Social Sciences
VH	Very High
VL	Very Low

List of Figures

List of Tables

CHAPTER 1: INTRODUCTION

Chapter 1 sets the foundational stage for this thesis by elucidating the crucial role of groundwater as a sustainable resource and delineating the challenges it faces under increasing environmental and anthropogenic strains. Groundwater's significance is highlighted in the context of Southeast Hungary, where agricultural practices and climate variables pose persistent threats to its quality and availability. The chapter discusses the intrinsic and specific vulnerabilities of aquifers, establishing the urgent need for comprehensive vulnerability assessments. By outlining the objectives and structure of the thesis, this chapter prepares the reader for a detailed exploration of various groundwater vulnerability assessment methods. It aims to bridge the gap between theoretical frameworks and practical applications necessary for effective groundwater management, emphasizing the development of tailored strategies to safeguard this vital resource against the backdrop of Southeast Hungary's unique hydrogeological challenges.

1. 1 Background and significances

Groundwater represents the world's largest accessible freshwater resource and sustains over half of the global population for both economic activities and daily survival (Jain, 2023). This vital resource replenishes naturally under most conditions, making it a renewable asset in the global water cycle (Mosavi et al., 2020). However, as global populations increase and anthropogenic activities intensify, groundwater faces significant threats from depletion and pollution, with clear detrimental effect. These challenges are compounded by the potential long-term impacts of climate change, which threaten to exacerbate these negative trends further (Aeschbach-Hertig and Gleeson, 2012). On top of that, aquifers in every part of the world receive today, the relentless discharge of waste and industrial effluents is overwhelming the natural purification capacities of the ecosystems, leading to the accumulation of pollutants deep within aquifers (Basu and Van Meter, 2014). Additionally, the widespread reliance on tube wells significantly contributes to groundwater contamination (Ghouili et al., 2021).

In the context of Southeast Hungary, which forms a part of the Great Hungarian Plain, the region is characterized by its flat and fertile plains that are predominantly utilized for agriculture. This sector forms the economic cornerstone of the area, encompassing over 65% of the land dedicated to cultivating crops such as maize, sunflowers, wheat, onions, and various fruits (General Directorate of Water Management in Hungary - OVF, 2021). The prevalent and intensive use of fertilizers and pesticides associated with these agricultural practices poses significant risks to the groundwater quality. Additionally, the region is susceptible to severe and prolonged droughts, further exacerbating challenges related to groundwater depletion and influencing the dynamics of the groundwater table (Rossi et al., 2023; Szöllősi-Nagy, 2022).

Given the multifaceted challenges, an integrated and multidisciplinary approach is essential to address the complex issues surrounding groundwater sustainability in Southeast Hungary. This approach must incorporate a variety of groundwater quality and vulnerability assessment techniques, which are deeply rooted in an extensive understanding of both local and regional geological contexts. A pivotal element of such approaches involves assessing the vulnerability of aquifers, particularly to leaching contaminant from surface to subsurface. This assessment is crucial as it serves not only to screen and manage groundwater resources effectively but also to facilitate the development of management plans that are specifically tailored to address the immediate and long-term sustainability needs of the region (Denizman, 2018; S. Foster et al., 2013). Understanding the specific vulnerabilities of aquifers is essential for crafting strategies that adeptly balance current developmental imperatives with the imperative of future resource sustainability. This strategic approach underscores the importance of a preventive framework that integrates scientific insights with practical management to ensure the enduring viability of groundwater resources (Focazio et al., 2003).

While numerous studies have focused on general groundwater quality and quantity in Southeast Hungary, there remains a significant gap in comprehensive, method-specific vulnerability assessments within this specific region. Previous studies, such as those by Pinke et al. (2020) on the sensitivity of wheat and maize yields to variations in groundwater levels, Gribovszki et al. (2017) on the impact of surface covers on groundwater uptake, and Barreto et al., (2017) on groundwater quality and quantity assessments, have provided foundational insights. However, these studies have not thoroughly explored the vulnerability of the aquifer system to a wide array of potential contaminants through diverse and comparative methodological frameworks such as DRASTIC, GOD, SI, and Fuzzy-enhanced DRASTIC. This gap highlights a critical need for an integrated approach that not only assesses but also compares the effectiveness of various vulnerability assessment methodologies in detailing specific susceptibilities of the region's groundwater system.

This research endeavors to address the identified gaps by conducting a detailed and comprehensive analysis of groundwater vulnerability in Southeast Hungary using multiple established methods. This study is unique in its comparative analysis of the DRASTIC, Fuzzy-enhanced DRASTIC, GOD, and SI methods, aiming to evaluate their efficacy in accurately assessing the vulnerabilities of the local aquifer system. The findings from this research will provide crucial information for stakeholders, policymakers, and scientists, enabling them to better understand the specific vulnerabilities of Southeast Hungary's aquifer. Such knowledge is crucial for developing strategic measures that effectively balance the needs of current agricultural and industrial activities with the long-term sustainability of groundwater resources. This research, therefore, provides essential information that will aid in the formulation of informed, strategic decisions aimed at protecting and managing the groundwater system more sustainably.

The subsequent chapters will build on this background by systematically exploring and comparing different groundwater vulnerability assessment methods. Chapter 2 will delve into a literature review of existing groundwater vulnerability assessment methods, focusing on their theoretical underpinnings, applications, and the role of GIS in enhancing their accuracy and applicability. Chapter 3 will outline the specific methodologies employed in this study, including the novel integration of established models with advanced analytical techniques. Chapter 4 will present the findings, discussing the implications of these assessments for sustainable groundwater management in the region. Finally, Chapter 5 will synthesize the insights gained, offering recommendations for policy, practice, and future research.

1. 2 Importance of groundwater

Groundwater is an indispensable component of the earth's hydrological system, occupying the pore spaces of soil and rock and fractures within rock formations beneath the earth's surface (Srebotnjak et al., 2012). Due to its subterranean nature, groundwater is generally less susceptible to contamination and pollution than surface water, making it a more stable and reliable source for domestic purposes. It undergoes natural filtration processes that eliminate bacteria and odors, thereby enhancing its quality for consumption (Pat M. Cashman and Martin Preene, 2021). As the largest reservoir of accessible freshwater, (26%) of the global renewable fresh water resources (FAO, 2021), groundwater's role extends beyond natural ecosystems to fundamental economic growth in both urban and rural areas globally (Cuthbert et al., 2019).

Due to its high percentage, reduced sensitivity to pollution, and large storage capacity, groundwater is pivotal at a socioeconomic level worldwide, providing about 50% of the world’s drinking water and supporting 40% of industrial needs with the remainder crucial for irrigation (Saha et al., 2024). In Hungary, where more than 90% of drinking water is sourced from deep aquifers and riverbank filtrations, the integrity of groundwater is especially significant (Engloner et al., 2019). However, despite its advantages, the challenge of sustainable management looms large, compounded by the high demand and limited recharge rates. This imbalance has led to declining water tables, deteriorating water quality, and increased incidence of land subsidence (Ahmad et al., 2017).

In Hungary, groundwater plays an important role in supporting drinking, industrial operations, and agricultural activities predominantly reliant on shallow aquifers. Annual consumption for irrigation alone amounts to approximately 42 million m^3, underscoring the critical dependence on this resource (Barreto et al., 2017).

Given these pressures, understanding and protecting groundwater resources become paramount. Aquifer vulnerability mapping emerges as a crucial strategy, enabling the identification of zones particularly susceptible to contamination from surface pollutants. This process not only enhances our understanding of the aquifer dynamics but also directs attention towards managing human activities that pose risks to these vital resources. By focusing on these vulnerable areas, tailored management strategies can be developed to safeguard groundwater, ensuring its sustainability for future generations.

1. 3 Overview of groundwater vulnerability

Introduced in the 1960s, the concept of groundwater vulnerability was developed to highlight the intrinsic purity often associated with groundwater. In other words, this term underscore the resource's susceptibility to external agents and susceptible to pollution (Margat, 1968). While widely recognized, the term 'groundwater vulnerability' lacks a formal accepted definition and standardized assessment methodology, because the concept of vulnerability is not an absolute property but a complex indicator (Maxe and Johansson, 1998). The formalization of this concept in hydrological literature did not occur until the 1970s (Albinet, M. and Margat, 1970), driven by global increases in groundwater contamination worldwide. Albinet and Margat (1970) characterized groundwater vulnerability as the susceptibility of the water table to surface pollutants, utilizing various parameters to assess how exposed the water table is to surface contaminants. Subsequently, multiple definitions have emerged. For example, the National Research Council (1993), p.1, defines it as *"groundwater vulnerability is defined as the tendency or likelihood of contaminants reaching the groundwater system after introduction at the surface and is based on the fundamental concept that some land areas are more vulnerable to groundwater contamination than others"*. Vrba and Zaporožec (1994), p.7 describes it as *"an intrinsic property of a groundwater system, depending on the sensitivity of that system to human and/or natural impacts".* Therefore, the term aquifer vulnerability refers to the degree to which a sub-surface system is likely to be adversely affected by any perturbation or stress from the land surface. This notion is based on the fundamental concept that some regions are more vulnerable to groundwater contamination compared with others (Jiradech M., 2013). This susceptibility is influenced by the natural attenuation capacity related to a set of physicochemical processes like filtration, biodegradation, hydrolysis, adsorption, dilution, volatilization, and dispersion (Stigter et al., 2006). Importantly, the vulnerability of aquifer zones to contaminants is considered a relative measure and is neither directly quantifiable nor dimensionless concept (Richts and Vrba, 2016).

The concept of groundwater vulnerability is based on the origin-pathway-target model, as illustrated in Figure 1, which is employed in a notable European initiative aimed at safeguarding aquifers. This initiative is part of a comprehensive European research program, 'COST Action 620, 2004 European Cooperation in Science and Technology' (Zwahlen, 2003). In this model, the 'origin' of contamination corresponds to the place of infiltration of contaminants at the land surface, while the 'target' refers to the groundwater in which its protection is the main subject. This target could either be the groundwater surface itself or a drinking water abstraction point (well/spring). The 'pathway' describes the route that contaminants travel through natural media (i.e., from an unsaturated zone to a saturated zone), from origin to target. This concept is developed to identify and prioritize areas within a basin that are most susceptible where groundwater contamination may occur. It establishes a robust scientific framework for the protection of groundwater resources and the management of land use. Two primary approaches for groundwater protection can be described. The first pertains groundwater as a 'resource', and aims to preserve the aquifer storage, whereas the second regards groundwater as a 'source' and aims to safeguard specific abstraction points, such as production wells and springs (Basu and Van Meter, 2014). However, the two concepts are closely linked in terms of protecting the source, which generally also means protecting the resource. Vulnerability maps of resources consider the groundwater surface as the target, and the unsaturated zone is treated as the pathway. If the object of protection is the source (i.e., a well or spring is considered the target), the pathway encompasses the horizontal flow path within the aquifer (Goldscheider, 2005). From a quantitative perspective, assessing vulnerability involves considering three critical factors: travel time for a contaminant from origin to target, the attenuation process of the contaminant along its pathway, and the duration of the presence of contamination at the target.

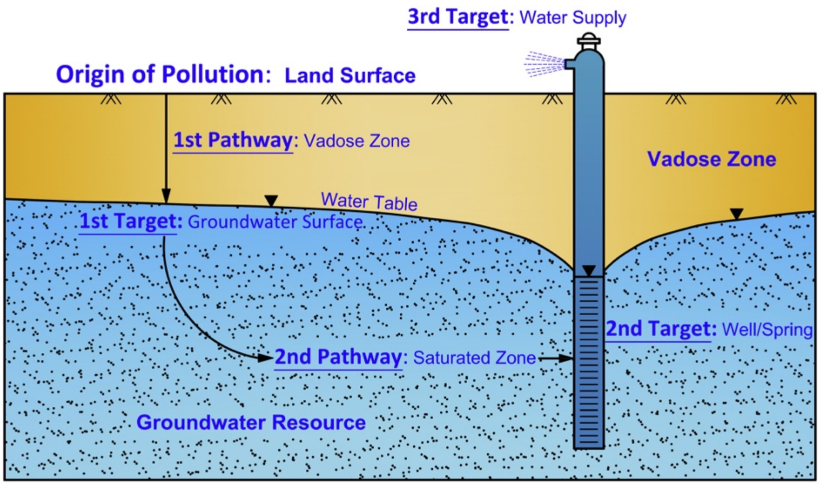


***Figure 1**. Conceptual framework illustrating 'Origin', 'Pathway', and 'Target' model for assessment groundwater vulnerability with emphasis on 'resource' and 'source' protection* (Machiwal et al., 2018)

The groundwater vulnerability is influenced by a multitude of factors, including natural phenomena in the region, such as rainfall and aquifer recharge, anthropogenic activities (e.g., land use, the use of agricultural chemicals, and mining), as well as the intrinsic properties of the aquifer system itself, such as the depth to water table, topography, net recharge, and the natural attenuation processes of the groundwater system (Wachniew et al., 2016).

The concept of groundwater vulnerability can be differentiated into two main notions, intrinsic and specific vulnerability. (i) Intrinsic vulnerability is used to represent the physical characteristics of the groundwater system (e.g., inherent geological, hydrological, and hydrogeological characteristics) that affect its susceptibility to contamination generated by anthropogenic activities regardless of the nature of contaminants (Civita, 1994; Wachniew et al., 2016). In the available literature, this type of analysis is the most frequently adopted because it does not include the comprehensive data required to assess the degradation processes that a pollutant could experience across different geological layers (Daly et al., 2002), (ii) specific vulnerability is used to define the susceptibility of groundwater to a selected contaminant or group of pollutants, considering the characteristics of the pollutants e.g. biogeochemical attenuation processes, and their interaction with the intrinsic properties of the groundwater system (Ribeiro et al., 2017). According to Vrba and Zaporožec (1994), this classification can be intricate, given the challenges associated with tracing the origins of pollutants.

This comprehensive understanding of groundwater vulnerability forms the foundation upon which this thesis is built. The subsequent chapters of this study will delve deeper into the application of various assessment methods specifically within Southeast Hungary, an area that presents unique challenges due to its agricultural intensity and hydrogeological characteristics

1. 4 Objectives of the study

The overarching goal of this research is to provide a comprehensive evaluation of groundwater vulnerability in Southeast Hungary, utilizing and comparing multiple assessment methodologies. The objectives are structured to critically analyze existing methods, improve the understanding of how different methodologies can influence vulnerability assessments, determine the most effective approach for local groundwater management strategies. The specific objectives of the study are as follows:

(1) Review of groundwater vulnerability assessment methods:

The objective of this component is to critically review existing approaches such as DRASTIC, GOD, and Susceptibility Index (SI) for assessing groundwater vulnerability. This review address the strengths and limitations of each method in the context of different hydrogeological settings providing a groundwork for subsequent analyses and methodological enhancements.

(2) Evaluate existing groundwater vulnerability assessment methods

Assess the suitability of the traditional DRASTIC, GOD, and Susceptibility Index (SI) methods to understand their strengths and limitations within the hydrogeological context of Southeast Hungary. This includes examining how these methodologies account for local variations in geology, hydrology, and human impact.

(3) Enhance the DRASTIC model using Fuzzy logic

The aim here is to enhance the traditional DRASTIC model using a Hierarchical Fuzzy Inference System (FIS) to address uncertainties inherent in the input parameters. This enhancement aims to provide a more accurate and nuanced assessment of groundwater vulnerability.

(4) Conduct a comparative analysis of groundwater vulnerability assessment methods and develop spatially explicit vulnerability maps

This objective involves a comparative analysis of the effectiveness and accuracy of the applied methodologies—DRASTIC, GOD, SI, and the Fuzzy-enhanced DRASTIC model—by examining their correlation with observed groundwater contamination indicators. The focus is particularly on nitrate concentrations. In parallel, Geographic Information Systems (GIS) is employed to generate spatially explicit vulnerability maps for each method, enabling visualization and interpretation of the results. This combined approach supports the identification of the most reliable methodology for the region and provides a valuable decision-support tool for groundwater protection and land-use planning.

(5) Inform policy and management strategies

This objective involves providing scientifically backed recommendations to local and regional policymakers and stakeholders on the adoption of appropriate groundwater management and protection strategies based on the findings from the comparative effectiveness of the assessment methodologies.

(6) Contribute to the global body of knowledge on groundwater vulnerability

Contribute to the scientific literature on groundwater vulnerability by providing insights into the application and modification of assessment methods in a specific regional context, thus offering a pathway for future research and methodology refinement.

CHAPTER 2: LITERATURE REVIEW

This chapter systematically reviews the existing methods and technologies employed in groundwater vulnerability assessment, setting the foundation for the applied methodologies discussed later in this thesis. It begins by exploring a variety of established groundwater vulnerability assessment methods, providing a contextual backdrop for more detailed discussions of specific methods. This will include a critical evaluation of the DRASTIC, GOD, and SI methods exploring their theoretical bases, limitations and practical applications, and then discussing the integration of fuzzy logic with DRASTIC to address uncertainties inherent in the input parameters, and the role of GIS in enhancing their accuracy and applicability.

2. 1 Groundwater vulnerability assessment methods

Groundwater serves as a crucial water source worldwide, supporting various purposes that span from domestic to industrial applications (Shirazi et al., 2012). However, challenges such as mismanagement, demographic growth, and the expansion of urban, agricultural, and industrial activities have heightened the risk of contamination to this vital resource (Serra et al., 2021). These factors, combined with the growing dependence on groundwater, underline the urgent need to develop comprehensive groundwater management strategies for its sustainable use and preservation (Foster et al., 2013). Assessing the vulnerability of aquifers is a pivotal approach for preserving and optimizing water resources now and in the future (Demiroğlu and Dowd, 2014). This evaluation is crucial for gaining a deeper understanding of which aquifers and regions are most susceptible to surface pollution. Within the framework of groundwater protection, three distinct approaches can be differentiated in evaluating groundwater vulnerability, each with its unique methodology for addressing contamination risks (Fannakh and Farsang, 2022; Machiwal et al., 2018). (i) The first approach focuses on the evaluation of vulnerability only by considering the soil and the unsaturated zone factors, excluding considerations of transport processes within the saturated zone. In this case, evaluation is limited to the relative possibility that contamination will reach the saturated zone. (ii) The second approach involves delineating protection zones for groundwater supply systems, where groundwater flow and transport processes in the saturated zone are considered to a certain extent. (iii) The third, more comprehensive approach encompasses both the soil and unsaturated zones as well as the saturated zones, providing a holistic evaluation of groundwater vulnerability. These approaches form the basis for a variety of groundwater vulnerability assessment methods, which differ significantly in their complexity, computational demands, and data requirements (National Research Council, 1993). The existing groundwater vulnerability assessment methods can be categorized into the following three broad categories (Fannakh and Farsang, 2022; Machiwal et al., 2018; Taghavi et al., 2022):

- Overlay and index-based methods,
- Process-based simulation methods, and
- Statistical methods.

These classifications and the specific methods under each will be discussed in detail in subsequent subsections.

2. 1. 1 Overlay and index-based methods

Overlay and index-based methods (qualitative methods), remain the most commonly employed models for groundwater vulnerability assessment due to their simplicity and effectiveness (Shrestha et al., 2017). These methods utilize a straightforward qualitative or semi-quantitative framework that principally depends on geological parameters. Within each methodology, different parameters are assigned numerical scores or ratings, which are then aggregated to form an overall groundwater vulnerability index (Moraru and Hannigan, 2018; Taghavi et al., 2023). The initial step involves identifying the soil, hydrogeological, hydrographical, and morphological characteristics that match each zone within a vulnerable range. Subsequently, the entire zone is evaluated and categorized based on predefined criteria (Goyal et al., 2021). Integration with Geographic Information Systems (GIS) enhances these methods, facilitating the overlay and indexing of maps within the spatial domain (Kaur and Rosin, 2009). This allows for the generation of vulnerability maps of medium-to-large areas, encompassing diverse hydrographic and morphostructural features, which makes it easier for the users to interpret the results (Kumar et al., 2015). Numerous overlay and index-based methods have been tailored in various countries to suit specific types of aquifers, namely, methods for porous aquifers or methods for karst aquifers (Jenifer and Jha, 2018; Jha, M.K., Peiffer, 2006). The three methods, which are the subject of this research, are DRASTIC (Aller et al., 1987), GOD (Foster, 1987), and SI (Ribeiro, L., 2000) methods used to assess aquifer vulnerability, are the widely used GIS-based overlay and indexing methods (Ghazavi and Ebrahimi, 2015; Ghouili et al., 2021; Machiwal et al., 2018).

Despite the simplicity aspects of overlay and index-based methods contributes to their widespread adoption, these approaches have significant drawbacks. The major limitation is the inherent subjectivity involved in selecting relevant parameters that influence groundwater vulnerability and assigning appropriate weights and ratings to each parametric map, which leads to significant uncertainties, and the lack of strong criteria for the classification of vulnerability (Gogu and Dassargues, 2000; Machiwal et al., 2018). Often, the weight and rate scores have been selected/modified based on the expertise and discretion of the researcher (Gogu et al., 2003). However, validating the vulnerability maps must be a required step and can be conducted using the water quality parameter. To reduce the risk of incorrect decisions, the objective of groundwater value assessment should always be as rigorous as possible (Oke, 2017; Zwahlen, 2003). Another drawback is the lack of consistency across different models when applied to a given region, highlighting the critical importance of choosing the appropriate method (Andreo et al., 2006; Pavlis et al., 2010). To address these inconsistencies, experts suggest that increasing confidence in vulnerability assessments involves comparing outcomes across various tools and corroborating these through case studies on areas, where contamination occurred (Stigter et al., 2006). Nonetheless, as Neukum et al. (2008) note, vulnerability levels typically expressed in qualitative terms like 'low,' 'moderate,' or 'high,' complicate direct comparisons of different models at the same site. For instance, (Richard et al., 2004) compared several approaches in porous media aquifer and in a fractured rock aquifer system and concluded that the vulnerability maps for a given hydrogeological system considerably vary according to the type of the selected method for vulnerability assessment. Notably, these approaches were primarily developed for unconfined aquifers and may not be suitable for confined aquifer systems (Goyal et al., 2021; Moraru and Hannigan, 2018).

A comprehensive summary of significate overlay, and index-based methods is presented in Table 1, which delineates each method's defining parameters, applicable aquifer types, vulnerability types, and protection strategies.

***Table 1**. Summary of significant overlay and index-based methods for evaluating groundwater vulnerability*

Methods	Defining parameters	Equation	Aquifer types	Protection strategies	GW vulnerability types	Sources
DRASTIC	depth to groundwater table (D); recharge rate (R); aquifer media (A); soil media (S); topography (T); impact of the vadose zone (I); and hydraulic conductivity (C)	$\mathrm{Vi} = \sum_{i=1}^{7} \mathrm{Wi\ Ri}$ Wi and Ri weight and rating for the ith parameter, respectively (range of parameters are given Aller et al., 1987)	Porous aquifers/ Karst aquifers	Resource protection	Intrinsic vulnerability	(Aller et al., 1987)
GOD	G = groundwater type, O = lithology for unsaturated zone, D = depth of groundwater	$I_{vGOD} = G_R \times O_R \times D_R$ R = rating of parameters	Porous aquifers/ Karst aquifers	Resource protection	Intrinsic vulnerability	(S. Foster, 1987)
Susceptibility Index (SI)	depth to water table (D); recharge rate (R); Aquifer media (A); topography (T); land use (LU)	$I_{vSI} = DnDp + RnRp + AnAp + TnTp + LUnLUp$ n = rating value for each parameter, p = weighting factor assigned to each parameter	Porous aquifers/ Karst aquifers	Resource protection	Specific vulnerability	(Ribeiro, L., 2000)

SINTACS	soggicenza (S) (means depth to groundwater); infiltration (I); non-saturo (N) (means unsaturated zone attenuation capacity); tipologia della copertura (T) (means soil attenuation capacity); aquifero (A) (means saturated zone characteristics); conductivity (C); surface slope topography (S)	$Vi = \sum_{j=1}^{7} (\mathrm{Pi} \times \mathrm{Wi})$ (Pj and Wj are rating and weight respectively)	Porous aquifers/ Karst aquifers	Resource protection	Intrinsic vulnerability	(Civita and De Maio, 2004)
GALDIT	groundwater occurrence (G); aquifer hydraulic conductivity (A); groundwater level above sea level (L); distance from the shore (D); the impact of the existing status of seawater intrusion (I); and thickness of the aquifer (T)	$I_{GALDIT} = \frac{\sum_{i=1}^{6}(Wi \times Ri)}{\sum_{i=1}^{6} Wi}$ Wi = weight of the ith indicator; Ri = rating of the ith indicator.	Coastal aquifer	Resource protection	Specific vulnerability	(Chachadi and Lobo-Ferreira, 2005)
EPIK	epikarst (E); protective cover (P); infiltration conditions (I); karst network development (K)	$F = \alpha Ei + \beta Pi + \gamma Ii + \delta\ Ki$ Ei, Pi, Ii, and Ki are classes assigned to each cell; α, β, γ, δ attribute relative weights; and i =1…, n is the grid cell number	Karst aquifers	Resource protection/ Source protection	Intrinsic vulnerability	(Jeannin et al., 1999)
AVI	D = thickness of each sedimentary unit, and K = estimated hydraulic conductivity of each sedimentary unit.	$c = \sum_{i=1}^{n} \frac{dj}{ki}$ (n = number of sedimentary layers above the aquifer)	Porous aquifers/ Karst aquifers	Resource protection	Intrinsic vulnerability	(Stempvoort et al., 1993)
COP	concentration of flow (C); overlaying layers (O); precipitation (P)	Ci = C× O × P	Karst aquifers	Resource protection	Intrinsic vulnerability	(Daly et al., 2002)
Slovene approach	overlaying layers (O); concentration of flow (C); precipitation (P); karst network development (K)	Iv = (O × C× P) + K	Karst aquifers	Resource protection/ S ource	Intrinsic vulnerability	(Ravbar & Goldscheide
PaPRIKA	protection factor (P); reservoir type (R); infiltration (I); karstification degree (Ka)	V_g = (i × I) + (r × R) + (p × P) + (k × Ka) (V_g is groundwater vulnerability index; i, r, p, and k are affecting weights)	Karst aquifers	Resource protection/ S ource	Intrinsic vulnerability	(Plagnes et al., 2010)

GW: Groundwater

2. 1. 2 *Process-based methods*

Contrary to the qualitative approaches, quantitative or process-based methods, these methods can be used to assess the vulnerability (typically, specific vulnerability) of aquifer using natural processes that occur in the hydrogeological parameters of underlying unsaturated and saturated zone systems (Focazio et al., 2003). These methods involve simulation models that integrate various physical, chemical, and biological processes to predict the transport of contaminants on the spatial and temporal scales. Furthermore, these methods emphasize the protection of the source and resource (Abokifa et al., 2020; Machiwal et al., 2018). The complexity of process-based methods can vary significantly, ranging from relatively simple functional models to complex models dependent on data requirements and the level of complexity (Schlosser et al., 2002). Advanced models can solve equations governing flow and transport processes in the unsaturated zone or aquifer porous media and can consider the stochastic nature of specific system parameters. For models intended to assess intrinsic vulnerability, parameters such as the thickness of the aquifer and site-specific hydrological regime can be used (Maxe L., Johansson, 1998). For instance, in process-based simulation utilizing MODFLOW, the groundwater body is segmented into cells using a two-dimensional or three-dimensional grid. Aquifer characteristics and all other features are then assigned to these cells, and the resulting model is solved by executing the program (Ghouili et al., 2021). The output information, such as groundwater velocity, hydraulic head and pollutant concentration, can be visualized in two or three dimensions (Aliyari et al., 2019; Madhavan et al., 2023).

In the literature, some of the quantitative approaches to assessing groundwater vulnerability include: MODFLOW (Arlen W. Harbaugh, 2005; Zhao et al., 2022), Root Zone Water Quality Model (RZWQ)M (DeCoursey et al., 1992; L. Ma et al., 2012), HYDRUS-1D (Vogel and Zhang, 1996), Water Assessment Tool (SWAT) (Aliyari et al., 2019; Arnold et al., 1998), FEMWASTE (Yeh and Tripathi, 1991), HYDRUS-2D/3D (Simunek et al., 2012), Pesticide Analytical (PE- STANS) (Enfield et al., 1982), and LEACHM (Hutson and Wagenet, 1989). A complete description of the process-based methods and their applications can be found in references (Machiwal et al., 2018; Taghavi et al., 2022).

The principal advantage of process-based models over overlay and index-based methods is their quantitative evaluation of groundwater vulnerability, and their ability to accurately model contaminant transport in spatial and temporal dimensions (Moraru and Hannigan, 2018). Unlike most index-based methods that focus on resource protection, process-based approaches evaluate the vulnerability of both the source and the resource founded on proven scientific laws (Oke, 2017). Despite their superior accuracy compared to qualitative methods, process-based models also face limitations, particularly their assumption that fractured or karst aquifers behave as continuous porous aquifer systems, which overlooks the existence of preferential flow pathways (Gogu and Dassargues, 2000). This omission can lead to inaccurate transit time distributions in the case of preferential flow (e.g., flow systems in a karst aquifer), a challenge that has been acknowledged in the literature (Gazis and Feng, 2004; Logsdon, 2002). Moreover, the high demand for detailed field data, which is often unavailable, limits the reliability of these models when data must be estimated indirectly (Machiwal et al., 2018). The requirement for high-resolution data also restricts the application of these models to relatively small areas, such as parts of an aquifer system (Sajedi-Hosseini et al., 2018).

2. 1. 3 Statistical methods

The application of statistical methods in groundwater vulnerability assessment started during the 1990s, these methods gained traction alongside GIS-based qualitative methods due to advancements in computer technology and the enhanced availability of geo-environmental data (Sorichetta et al., 2013). The statistical methods provide a viable means for assessing aquifer vulnerability when groundwater quality data are linked to media data that affect groundwater contamination (e.g., hydrogeological data, soil properties, land use, and human activities) (Jain, 2023). These methods can range from simple descriptive statistics of the concentrations of contaminants to more complex regression analyses that incorporate the effects of several explanatory variables (Machiwal et al., 2018). Simple descriptive statistical approaches are commonly used to summarize point data and produce point maps that illustrate the presence and spatial distribution of contaminants, providing the basis for more complex analyses that explore the correlation between geological settings and point data (Mendoza & Barmen, 2006). More rigorous statistical analyses, such as logistic regression (which intends to account for potential explanatory variables), additional information and data are frequently included as potential sources of contamination and factors that influence the intrinsic susceptibility of resources (Schleyer, 1994).

According to (Machiwal et al., 2018; Taghavi et al., 2022), the most commonly used statistical techniques in the evaluation of vulnerability are: (i) logistic regression or binary logistic regression, which are useful methods for assessing the vulnerability of aquifers to pollution by different contaminants, such as nitrate, chloride, and pesticides, it predicts the likelihood of a contaminant's presence, categorizing outcomes as binary (true or false) rather than continuous values (Lonna et al., 2012). (ii) Multiple linear regression (MLR), which is conceptually similar to the logistic regression method. The MLR method conceptually evaluates the relationships between a dependent factor and several independent factors and predicts the concentration of contamination instead of the probability of pollution (Stackelberg et al., 2012; Steichen et al., 1988). It is useful for comparing drinking water standards. Lastly, (iii) artificial intelligence (AI) models, such as: fuzzy logic, artificial neural networks, and neuro-fuzzy modeling, which have been applied in the prediction of groundwater vulnerability (Dixon, 2005; Gesim & Okazaki, 2018). Fuzzy logic and fuzzy set theory are mainly used in fuzzy input modeling, because they account for imprecision and uncertainty and reduce information loss when coupled with GIS-based methods (F. Wang et al., 1990); other (AI) models that are powerful soft-computing methods and are highly limited in water resources studies (Rodriguez-Galiano et al., 2014), such as Random Fores (Judeh et al., 2022), and Support Vector Machine (SVM) (Elzain et al., 2022; Khan et al., 2022; Sajedi-Hosseini et al., 2018). A complete description and a number of statistical methods used for groundwater vulnerability assessment, with several relevant studies can be found in references (Jain, 2023; Machiwal et al., 2018; Taghavi et al., 2022).

While statistical methods excel at identifying complex relationships between variables, managing uncertainties, and predicting contamination probabilities, they also pose significant challenges. The major challenge is selecting the most suitable statistical model, it is complex to design and, once developed, the model comes with its own set of assumptions. Consequently, their applicability is generally limited to regions with environmental conditions similar to those where the model was originally formulated (Oke, 2017). Furthermore, they require substantial data inputs, making them both costly and time-consuming to implement effectively (Jain, 2023; Machiwal et al., 2018). Despite these challenges, the capacity for using statistical methods to enhance GVA is substantial, meriting further investigation and application.

2. 2 Principle of application of the DRASTIC, GOD, and SI approaches for assessing groundwater vulnerability

2.2.1 DRASTIC method

2.2.1.1 Overview of the DRASTIC method

The DRASTIC method is a systematic approach developed in 1987 under a cooperative agreement between the United States Environmental Protection Agency and the National Water Well Association (Aller et al., 1987) for assessing groundwater vulnerability through an index and rating system. This method integrates seven critical hydrogeological factors that determine an aquifer's sensitivity to potential contaminants. These factors are depicted in Figure 2 and described in Table 2.

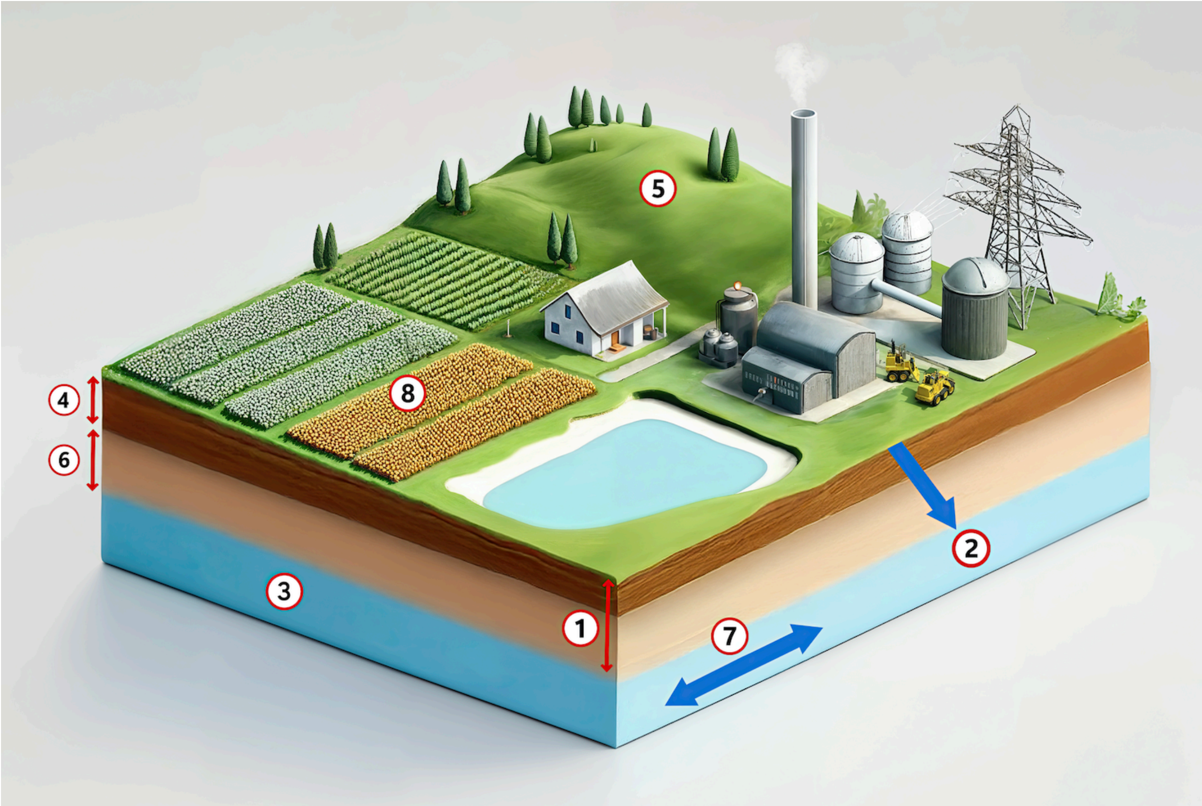


***Figure 2**. Thematic data layers required for mapping groundwater vulnerability using the DRASTIC, GOD, and Susceptibility Index (SI) models: (1) Depth to water table; (2) Aquifer recharge; (3) Aquifer media (or aquifer type); (4) Soil media; (5) Topography (slope); (6) Impact of the vadose zone; (7) Hydraulic conductivity; and (8) Land use/land cover.*

***Table 2**. Parameters and weights used by the index-overlay methods to calculate their vulnerability indices* (Aller et al., 1987; Foster, 1987; Ribeiro, L., 2000)

Parameters		Description/relationship with vulnerability	weight		
			DRASTIC	GOD	SI
D	Depth to water table	• A deeper water table implies longer travel times and less chance of contaminants reaching the aquifer.	5	1/3	0.186
R	Recharge	• A high recharge rate leads to a high probability of contaminant transport vertically to the water table and horizontally within the aquifer, increasing vulnerability to pollution.	4	-	0.212
A	Aquifer media (or Aquifer type)	• Refers to the saturated zone system, serving as an aquifer. The flow system within the aquifer controls the pollutant attenuation processes. Larger granulometry and greater permeability within an aquifer contribute to the greater vulnerability of groundwater to pollution.	3	1/3	0.259

		• For GOD schemes, it indicates the type of groundwater occurrence (G)			
S	Soil media	• Refers to the uppermost portion of the vadose zone which controls the recharge rate, thereby influencing the ability of a contaminant to transfer vertically into the unsaturated zone.	2	-	-
T	Topography (slope)	• Indicate the slope variability of the land surface. A slight slope will determine a high retention time for surface water, a higher likelihood of more recharge of the aquifer system, and effects on the pollutant transport.	1	-	0.121
I	Impact of the vadose zone	• The type of material in the vadose zone determines the attenuation characteristics that could have an effect on the passage and attenuation of the contaminant, depending on its permeability and the attenuation characteristics of the medium, affecting the available time for mitigation and the quantity of material encountered. • With the GOD approach, the overlying lithological characteristics of the unsaturated zone in terms of lithology and porosity refer to the overlying lithology (O).	5	1/3	-
C	Hydraulic conductivity	• Refers to the capacity of aquifer medium to transmit water, the rate at which groundwater flows control the rate at which contaminating materials are transmitted through the aquifer system.	3	-	-
LU/LC	Land use/cover	• Indicated that higher industrial and wastewater pollution, pesticides and fertilizers, a higher risk of contaminant materials being transmitted into the aquifer	-	-	0.222

2.2.1.2 Hypothesis

Aller et al., (1987) hypothesized that the transport of contaminants in groundwater systems is primarily governed by the movement of groundwater itself. In this framework, a conservative contaminant is assumed to migrate at the same velocity and in the same direction as the groundwater flow. This simplifying assumption allows the DRASTIC method to focus on hydrogeological parameters that influence groundwater flow rather than contaminant-specific properties. Whereas the study area considered has a surface area of more than 40 hectares. In other words, it is considered the probability of contaminants released from the surface to reach the groundwater system. It focuses on contamination from anthropogenic sources and does not assess pollutants introduced into the shallow or deep subsurface by certain processes, such as leakage from underground storage tanks, animal waste lagoons, or injection wells (Machiwal et al., 2018). The DRASTIC model employs a systematic rating and weighting system designed to predict vulnerability based on seven key hydrogeological factors. Each factor/parameter is evaluated on a scale from 1 (the aquifer system is not sensitive to that parameter) to 10 (indicating high vulnerability of the parameter) and assigned a corresponding weight from 1 to 5 based on its significance in affecting overall groundwater vulnerability (Aller et al., 1987). Theoretically, each parameter within the DRASTIC index acts as an independent variable, representing specific process or condition related with the leaching process within a seven-dimension space. The comprehensive integration of these parameters through the DRASTIC index provides a nuanced representation of groundwater vulnerability, allowing for a spatially differentiated assessment of intrinsic vulnerability (Rama et al., 2022).

2.2.1.3 Salient applications

As previously discussed, DRASTIC is one of the widely used methods for assessing the vulnerability of groundwater resources due to its performance and ease of applicability. According to local needs and to improve the results of the DRASTIC method, two principal approaches for modifying the DRASTIC method are possible:

(1) Modifying the weights and ratings on the basis of the thorough scientific analysis of data and the combination of the risk and vulnerability maps. Sahoo et al., (2016) identified three methods, namely, entropy information method (E-DRASTIC), fuzzy pattern recognition method (F-DRASTIC), and single-parameter sensitivity analysis (SA-DRASTIC), and applied them to Kanpur City, India. Furthermore, the authors changed the weights of the initial DRASTIC parameters to obtain the corresponding vulnerability index and compared the performance of the subjective (DRASTIC and SA-DRASTIC) and objective (E-DRASTIC and F-DRASTIC) weighting-based methods. The authors concluded that the objective approaches were suitable for vulnerability assessment in the study area. The effectiveness of E-DRASTIC and F-DRASTIC is based on the modification of the weights of only those parameters that are

essential in the vulnerability estimation process, as well as the objective methods assigning weights to features according to their relative importance in the final vulnerability assessment. Grey incidence analysis models have been used to evaluate the effectiveness of the modified DRASTIC methods. To improve the reliability of the model, Jafari and Nikoo, (2019) modified the DRASTIC model by adjusting the rating and weighting scores using Wilcoxon's rank-sum test and the fuzzy optimization model for groundwater risk assessment and by considering the nitrate concentration. The results demonstrate that the correlation coefficient between the original and improved DRASTIC models and nitrate concentration indicates that this approach is effective in improving the accuracy of the assessment of groundwater risk (i.e., the correlation coefficient increased significantly from 0.573 to 0.789).

(2) Altering the original DRASTIC parameters, such as subtracting parameters, or including other parameters, such as land use and irrigation type. Under the conditions of intense agricultural activities in Tiruchirappalli district, India, Jenifer and Jha, (2018) modified the original DRASTIC and pesticide DRASTIC (DRASTIC-P) models by introducing two extra parameters, namely, land use/land cover (LU/LC) and lineament density (LD), and compared them with six modified forms of these models, namely, DRASTIC-LD, DRASTIC-LU, DRASTIC-LDLU, DRASTIC-P-LD, DRASTIC-P-LU, and DRASTIC-P-LDLU. The results of the vulnerability maps generated by the eight vulnerability models were verified using a single water quality parameter (NO_3^- -N, F^- and Cl^-) individually. The performance of DRASTIC-P-LDLU indicated that the model is the most accurate one with accuracies of 61% and 68% for nitrate and chloride concentrations, respectively, followed by DRASTIC-LDLU with accuracies of 59% and 61% for the same concentrations. Other comparative studies conducted worldwide are presented in Table 3.

2.2.1.4 Advantages

Evidently, DRASTIC is one of the most widely known and used method for the assessment of aquifer vulnerability (Jain, 2023). It has been applied from municipal, such as National Capital Territory, Delhi, India (Tomer et al., 2019) to the continental scale, whereas the study developed by Rama et al., (2022) uses a critical application of the DRASTIC method to assess the intrinsic vulnerability of South American groundwater. The main strength of the DRASTIC method is its flexibility; the model allows for including or eliminating parameters or factors to adapt to different challenges, such as the conditions in the area of study and availability of data (Fritch et al., 2000; Jenifer & Jha, 2018; Sarkar & Pal, 2021; Singh et al., 2015; Singha et al., 2019). This adaptability extends to modifying the weight and rate scores depending on the field measurement data, enhancing the utility of susceptibility and risk maps when combined with DRASTIC (Khosravi et al., 2018). Over the past decade, several scientists have modified the original DRASTIC model by modifying the scoring ranges and relative weights and by including or omitting certain factors. However, Hamza et al., (2015) demonstrated that all parameters exert an equal influence on groundwater contamination, where each factor indicates a situation where it has exerted the greatest impact regardless of the weight assigned to the parameters.

Furthermore, the DRASTIC approach is a useful tool for assessing groundwater vulnerability, because it is relatively low-cost and simplicity. It utilizes data that are widely available or estimated, and its integration Geographic Information Systems (GIS) facilitates the creation of clear, easily interpretable maps that can be seamlessly incorporated into decision-making processes (Maxe and Johansson, 1998).

2.2.1.5 Limitations

The major limitations of the DRASTIC method are: (i) the reliability of the different parameters used by the approach is dependent on data used in their realization. Typically, information related to parameters, such as net recharge, hydraulic conductivity, water body depth, unsaturated zone impact (Kouz et al., 2020), and the penetration of contaminants through the vadose zone, are influenced by its lithology and determined through interpolation (Barbulescu, 2020; Cherkaoui Dekkakki H., 2006). This aspect leads to faults in the generation of parameter values because it is only accurate in the intervals delimited by the point data (Francés et al., 2002). Thus, the DRASTIC model can only be used as a relative assessment tool and is not designed to provide an absolute assessment of groundwater vulnerability (Ouedraogo, 2017). (ii) The one-dimensional DRASTIC approach may be sufficient for assessing the vulnerability of an aquifer in porous media, where water and contaminants penetrate vertically from the soil surface to the water table. Nevertheless, the opposite is true for karst aquifers, where water and contaminants bypass the protective function by flowing laterally through shallow holes (Oke, 2017). (iii) A few factors are overlapping, such as aquifer media and hydraulic conductivity, which is directly dependent on aquifer media, this can complicate independent variable analysis (Oke, 2017). (iv) The DRASTIC method does not consider the dilution within groundwater system, although it has a strong control on the levels of contamination, which may lead to erroneous results (Aller et al., 1987).

Table 3. *List of comparative studies of groundwater vulnerability assessment methods across different regions.*

Authors	Study area	Year	Methods used	Type of aquifer system	Results
(Polemio et al., 2009)	Apulia, southern Italy	2009	GOD, DRASTIC, SINTACS, EPIK, PI, and COP	Karstic aquifer	The GOD model gives an underestimation of vulnerability and a low sensitivity to spatial variation in key hydrogeological features. The DRASTIC and SINTACS approaches chose limitations in applications to karst aquifer systems. However, the methods EPIK, PI and COP, developed for application to carbonate or karst aquifers, provide cost-effective results, highly consistent with karst and hydrogeological characteristics.
(Majour et al., 2016)	Miopliocene sandy aquifer, Biskra, Algeria	2016	DRASTIC and SI	Porous media aquifer	By integrating the land use parameter, the results obtained with the SI model were more reliable compared to the DRASTIC model. The vulnerability maps produced were tested and validated by the distribution of groundwater nitrates in the study area. The correlation coefficient between the SI and the nitrate concentrations was 85%, which is higher than the 75% obtained with the DRASTIC method
(Ben-daoud et al., 2013)	The aquifer of the city of Meknes, Morocco	2013	DRASTIC and GOD	Porous media aquifer	The analysis of the results obtained from the DRASTIC and GOD approaches indicated three spatial distributions of vulnerability categories, Low, Medium and High, with 85% of similarity between the two methods for the medium vulnerability category
(Kouz et al., 2020)	Ghiss-Nekkour aquifer, Northeast of Morocco	2020	DRASTIC, GOD and SI	Porous media aquifer	The application of the DRASTIC, GOD and SI methods shows a range of intervals divided into categories corresponding to fluctuating degrees of vulnerability ranging from "very low" to "extreme". The validation of the mapping result was carried out using the nitrate concentrations measured in April 2017. The most reliable results were obtained with

					the SI method in comparison with DRASTIC and GOD
(Shrestha et al., 2017)	shallow groundwater aquifer of the Kathmandu Valley, Nepal	2022	DRASTIC, GOD and SI	Porous media aquifer	The DRASTIC and SI models are similar for the vulnerability assessment because both methods identify about 80% of the groundwater basin area under the highly vulnerable zone. By contrast, in the GOD model, vulnerability assessment identify areas with "low" and "moderate" vulnerability categories are 24% and 76% respectively. The correlation between the estimated risk and the measured nitrate concentration was performed to validate the resulting mapping. Comparing with DRASTIC and GOD, the authors conclude that the SI method has more reliable results
(Kirlas et al., 2022)	Nea Moudania aquifer, Chalkidiki, Greece	2022	DRASTIC, Pesticide DRASTIC, SINTACS, Nitrate SINTACS, GOD, AVI, and SI,	Porous media aquifer	As the study area is marked by intensive agricultural activities. The authors confirm that DRASTIC Pesticide and SINTACS Nitrate were the more precise and efficient methods for evaluating the groundwater vulnerability in the study area. Using the coefficient of correlation (R^2), the authors validated the results obtained by the seven methods using the nitrate concentrations from 23 observation wells. The most efficient and accurate approaches were Pesticide DRASTIC and Nitrate SINTACS with R2 = 0.6475 and 0.6438, respectively. The two methods have a slightly higher coefficient of determination compared to DRASTIC and Normal SINTACS. Besides, AVI, GOD methods were the less reliable, with correlation coefficients of GOD (R2 = 0.5348), AVI (R2 = 0.5045); SI method, which incorporates the land use parameter exhibited a greater R2 of 0.6084.

2.2.2 GOD Method

2.2.2.1 Overview of the GOD method

The GOD method, developed by Foster, (1987), provides a straightforward and effective framework for assessing groundwater vulnerability, particularly suited to regions with limited data availability (Kumar et al., 2015). It evaluates the vulnerability based on three primary parameters: Groundwater occurrence (G), Overlying lithology (O), and Depth to the groundwater table (D). This method has been widely applied in various hydrogeological studies around the world, proving particularly useful in preliminary assessments where detailed data may not be readily available, thus helping to prioritize areas for more intensive study or immediate management action (Alsharifa, 2017).

2.2.2.2 Hypothesis

The GOD method employs an empirical approach, where the vulnerability of aquifers is defined as a function of the inaccessibility of a saturated zone, in the sense of pollutant penetration, and the attenuation capacity of the layer above the saturated zone (Machiwal et al., 2018). This approach assumes that the vulnerability is directly influenced by the physical properties of the materials above the aquifer, which control how rapidly contaminants can reach the saturated zone (Goyal et al., 2021). In the GOD scheme, each of the factors—groundwater occurrence, overlying lithology, and depth to groundwater—are treated equally without differential weighting, reflecting their presumed uniform impact on the vulnerability of the aquifer (Foster, 1987; Jain, 2023; Machiwal et al., 2018).

2.2.2.3 Salient applications

Although the GOD method is less popular than the DRASTIC model, it has been applied in several specific studies (Jain, 2023; Machiwal et al., 2018). Ghazavi and Ebrahimi, (2015) assessed the vulnerability of the Abarkooh aquifer in southeastern Yazd province, Iran, using both the DRASTIC and GOD models. The authors used nitrate concentration as the primary pollution parameter to validate the vulnerability maps produced by these models. The study concluded that the DRASTIC method was more appropriate for the assessment of the potential for contamination in the study area compared with the GOD method. The correlation coefficient between the DRASTIC index and nitrate content was 68%, which is clearly exceeded the 28% obtained using the GOD method. In the alluvial aquifer of the Florina basin, Northern Greece, Kazakis and Voudouris, (2011) compared among three methods, DRASTIC, GOD, and AVI. Nitrate concentrations in groundwater were examined to verify the results obtained. Their findings suggested that the GOD approach displayed a correlation higher than those of the two other approaches, whereas the vulnerability map produced are generally comparable with the DRASTIC and AVI methods. Sayed et al., (2023) conducted a comprehensive groundwater vulnerability assessment using GIS-based DRASTIC and GOD methods in the industrialized peri-urban area of Araihazar Upazila, Bangladesh. The study highlighted that the DRASTIC model, by incorporating a broader set of hydrogeological parameters, produced a more detailed classification of vulnerability zones. In contrast, the GOD method, owing to its simplified and conservative framework, indicated substantially lower vulnerability levels, classifying 58% of the area as negligible and the remainder as low. A compilation of some comparative studies conducted worldwide can be found in Table 3.

2.2.2.4 Advantages

Although the GOD method is not as widely adopted as the DRASTIC method, it remains one of the best GIS-based overlay and indexing methods, mainly used in data-limited regions that require a rapid assessment of the groundwater situation, which can be applied in prioritizing management and protection efforts in vulnerable areas (Goyal et al., 2021; Sukmawati Rukmana et al., 2020). The major advantage of the GOD method is that it can be applied to any type of aquifer, except for those in karst regions. It is particularly effective in large-scale environments characterized by significant variations in vulnerability (Gogu and Dassargues, 2000; Kumar et al., 2015; Polemio et al., 2009).

2.2.2.5 Limitations

The GOD method, while effective, presents certain limitations. In regions with moderate variations in the level of vulnerability, the GOD method can provide homogeneous distributions of values. Thus, using this method in areas with high contrasting vulnerability is preferable (Gogu and Dassargues, 2000). Another limitation is the neglect of the inherent heterogeneity of underground systems, whereas the nature of the subcutaneous zone and vertical wells are additional problems when applying this method in karst areas (Machiwal et al., 2018; Oke, 2017). Addressing these issues, Foster, (1998) recommends adopting specific strategies in vulnerability assessments, such as using the predominant lithology of the layers above the aquifer; considering aquifers as unconfined in the case of doubts about the continuity and properties of the confining beds; and using shallow aquifers to assess pollution risk, except in the case of small-perched aquifers. Furthermore, the GOD method assumes a uniform impact of parameters on the vulnerability of the aquifer. This assumption can lead to the oversimplification of complex hydrogeological variations, potentially obscuring critical local details that are essential for accurate vulnerability assessments (Goyal et al., 2021).

2.2.3 Susceptibility Index (SI) approach

2.2.3.1 Overview

The Susceptibility Index (SI) method, developed by Ribeiro L., (2000), offers a refined approach to groundwater vulnerability assessment, particularly focusing on vertical contamination risks from agricultural activities. Unlike broader models, the SI method specifically integrates land use factor alongside traditional hydrogeological parameters, making it adept at addressing the impact of human activities on aquifer system (Ghouili et al., 2021). Developed for medium to large-scale assessments (scales ranging from 1:50,000 to 1:200,000) (Ribeiro et al., 2017), the SI method considers five parameters (Table 1). Each parameter is assigned a rating and weight that reflects its influence on contamination potential, with Land use acting as a dynamic factor that adjusts the vulnerability assessment to mirror actual land surface conditions, and the SI vulnerability index (I_{vSI}) is computed by linearly combining the scores and weights of the five parameters.

2.2.3.2 Theoretical basis of the SI method

The Susceptibility Index (SI) method is founded on a theoretical framework that integrates both hydrogeological and anthropogenic factors to assess groundwater vulnerability (Stigter et al., 2006). Recent studies emphasize the significance of including land use as a crucial factor in evaluating groundwater quality, highlighting its role in predicting the impact of human activities on aquifer system (Shrestha et al., 2017; Teixeira et al., 2015). At its core, the SI method enhances traditional vulnerability assessment by specifically considering land use patterns alongside natural hydrogeological parameters (Oke, 2017).

Ribeiro (2000), posits that the two factors, namely, the lithology of aquifer media and soil media exert no significant impact on the pollutant movement to the groundwater table. Additionally, aquifer media and hydraulic conductivity are two overlapping factors. Hydraulic conductivity is directly dependent on the characteristics of the aquifer media, complicating its independent evaluation (Engel et al., 1996; Oke, 2017). Consequently, the SI method excludes parameters such as soil media (S), the unsaturated zone (I), and aquifer hydraulic conductivity (C) from its assessment criteria.

The SI method assigns varying degrees of susceptibility based on the potential for contaminants, such as nitrates and pesticides, to migrate vertically through the materials above the aquifer system. Each parameter within the SI model—Depth to water table, Recharge rate, Aquifer media, Topography—is evaluated for its potential to facilitate or hinder this vertical movement (Ghouili et al., 2021). The inclusion of land use as a dynamic parameter allows the adjustment of vulnerability scores to accurately reflect local conditions such as agricultural intensity, urban development, and other land configurations that directly influence the protective capacity of the aquifer and the risk of contamination.

2.2.3.3 Salient applications

In recent years, aquifer vulnerability assessed using the SI model has many applications. For instance, Ribeiro et al., (2017) assess the groundwater vulnerability of the Daule aquifer in Ecuador using the Susceptibility Index (SI) method for diffuse agricultural pollution as a specific vulnerability method. The study finding, indicate that regions with high recharge rates and extensive agricultural activities, particularly paddy fields, are most high-vulnerability zones. Moderately vulnerable to low-vulnerability zones correspond to less disturbed natural areas like forests and semi-natural zones. The study proposes the implementation of a monitoring network to validate the SI map using nitrate concentration data, emphasizing the need for integrated groundwater management to protect water quality effectively. In the Takelsa phreatic aquifer, North-East of Tunisia, Ghouili et al., (2021) applied the SI approach to assess the vulnerability of groundwater. The resulting vulnerability maps were validated by comparing areas at high risk of salinity with their relative vulnerability index. Moreover, (Ghouili et al., 2021) demonstrated that 50% of the study area is characterized by areas of high to very high levels of vulnerability. The main reasons for these high-vulnerability areas are the presence of high recharge rates, sandy soils, shallow water tables, and areas with high levels of agricultural activity in land use. Moreover, comparative studies by Kouz et al., (2020) and Hamza and Added, (2009) have shown the SI method to yield more reliable results than the DRASTIC model, the vulnerability classes mapped are higher with the application of the SI approach, which supports the idea that the SI method was designed to consider the properties of nitrates and the relationship between them and intrinsic vulnerability. By contrast, the DRASTIC model ignores the nature of contaminants and focuses solely on hydrogeological parameters. This integration of various spatial features through the land use parameter enhances the method's applicability and accuracy in vulnerability assessments. List of some comparative studies conducted worldwide are given in Table 3.

2.2.3.4 Advantages

The main advantage of the Susceptibility Index (SI) method, its ability to incorporate land use changes as a parameter directly into the groundwater vulnerability assessment gives it a distinctive edge in accurately reflecting the specific vulnerability due to human activities (Brindha & Elango, 2015). This feature is crucial in agricultural regions where pesticide and nitrate usage heavily influence groundwater quality (Francés et al., 2002). Additionally, the SI model can be combined with Geographic Information Systems (GIS) and remote sensing to develop an integrated approach, especially for heterogeneous media that consider geological, hydrological, and geochemical data to improve the reliability of risk assessment (Anane et al. 2013; Bartzas et al. 2015). Similar to the DRASTIC and GOD methods, the SI approach was developed to assess the vulnerability of aquifers on large and medium scales.

2.2.3.5 Limitations

In the Nabeul-Hammamet aquifer, Tunisia, Anane et al., (2013) applied this method in combination with consistency, where contamination by nitrate has occurred. Data on vulnerability exhibited certain limitations in assessing groundwater vulnerability. The first is that the application of the SI model displayed an overestimation of vulnerability due to not accounting for the dilution effect, which can significantly mitigate the level of contamination. Moreover, (Noori et al., 2019) highlighted the difference between the most vulnerable and most contaminated areas. The second limitation is that the SI method overlooks the recycling process of groundwater that contributes to the accumulation of pollutants. This tendency leads to an underestimation of vulnerability due to the failure to consider two factors, namely, soil media and unsaturated zone (Anane et al., 2013). By not incorporating these parameters, the SI method potentially underestimates vulnerability where these factors play a significant role in contaminant filtration and attenuation. This oversight can lead to inadequate protection measures for aquifers that are more susceptible than the SI method suggests, particularly in regions where the soil media and unsaturated zones are key barriers to pollutant migration.

2. 3 Integration of fuzzy logic with the DRASTIC method

2.3.1 Overview

Fuzzy Logic (FL), introduced by Zadeh (1965), is an advancement over classical set theory that enhances the handling of imprecision by (i) extends classical set theory by removing strict boundaries typically associated with classical sets; and (ii) by redefining set membership of an object as a gradient from 0 (completely false) to 1 (completely true), rather than as a binary condition (Demicco and Klir, 2003). Membership Functions (MFs) characterize these fuzzy sets with uncertain boundaries that facilitate smooth transitions between categories to better manage the inherent uncertainties often found in complex systems (Grande et al., 2010). Fuzzy Logic is particularly effective in handling the ambiguities and imprecision commonly encountered in environmental, hydrological, and hydrogeological factors subject to uncertainty and ambiguity (Nourani et al., 2023). Within the domain of groundwater vulnerability, fuzzy logic refines the DRASTIC model by integrating qualitative expert insights with quantitative data into a comprehensive evaluative framework (Nadiri et al., 2017).

The operational framework of FL in this application comprises three pivotal stages (Fig. 3): (i) fuzzification, (ii) fuzzy inference (fuzzy rule base), and (iii) defuzzification, as described by (Zadeh, 2015). During fuzzification, crisp input values are converted into fuzzy sets to build the foundation of the inference system. The fuzzy inference mechanism employs a series of logical rules that relate these inputs to outputs, primarily using operations such as AND (minimum) and OR (maximum) to synthesize these relationships. This rule-based system integrates the fuzzy inputs into a unified output set through an implication process, which is then processed to deliver a singular decision outcome. The final stage, defuzzification, involves converting the fuzzy output back into a precise scalar value, completing the transition from fuzzy data inputs to actionable crisp outputs.

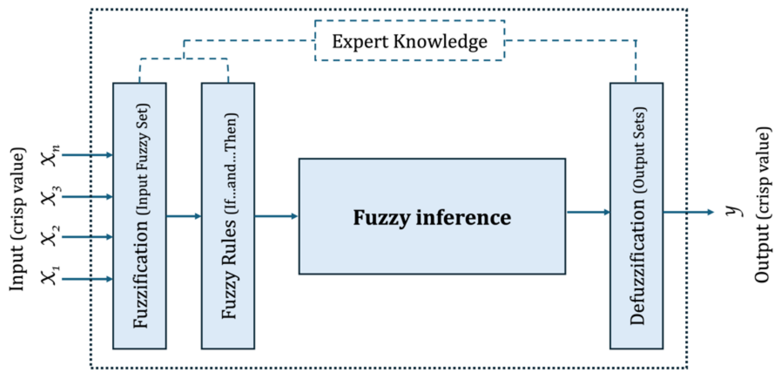


Figure 3. *Fuzzy logic system*

2.3.2 Methodological enhancements

As previously discussed, while DRASTIC effectively simplifies complex hydrogeological settings into an accessible index format and is widely adopted to evaluate vulnerability in different parts of the world (Barbulescu, 2020; Rama et al., 2022). Nonetheless, the inherent subjectivity of the data availability and/or the variability in hydrogeological characteristics across different regions require modifications to the DRASTIC model to enhance its accuracy, as evidenced by global studies on its adaptations (Baki and Ghavami, 2023; Huan et al., 2012; Javadi et al., 2011; Nguyen and Tat, 2024; Sener and Davraz, 2013; Thirumalaivasan et al., 2003; Torkashvand et al., 2023).

One of the persistent challenges of the DRASTIC model lies in its reliance on fixed parameter ratings, which often fail to capture the variability and uncertainty inherent in hydrogeological conditions (Saranya and Saravanan, 2021). Moreover, despite the need for a comprehensive set of input data for a thorough assessment of groundwater vulnerability, the data available for DRASTIC are often limited or compromised by the use of substandard measurement technologies (Taghavi et al., 2023). Fuzzy techniques are commonly used to overcomes these limitations by introducing flexibility and adaptability into the parameter ratings process (Das and Pal, 2020; Nadiri et al., 2017; Saranya and Saravanan, 2022). These techniques employing pseudo-trapezoidal membership function (MF) in conjunction with Mamdani inference and center-of-gravity defuzzification to establish linguistic definitions for DRASTIC indices. Building on this foundation, this study introduces an adaptation called the fuzzy-enhanced DRASTIC method, which integrates FL into the traditional DRASTIC method by employing hierarchical fuzzy inference systems (FIS) that enable dynamic adjustments to parameter ratings. This adaptation leverages expert knowledge and site-specific data to define fuzzy membership functions, allowing for a more nuanced representation of each parameter's impact on groundwater vulnerability. Unlike the static ratings of the original model, these fuzzy-enhanced ratings are dynamic, allowing for more nuanced categorizations and continuous transitions between vulnerability classes. The hierarchical FIS further augments this capability by processing the DRASTIC parameters simultaneously through a rule-based framework that captures the complex interrelationships among them. This results in a more comprehensive and context-sensitive evaluation of groundwater vulnerability (Jesiya and Gopinath, 2019; Saranya and Saravanan, 2021).

These methodological enhancements make the fuzzy-enhanced DRASTIC model a robust tool for groundwater vulnerability assessment, particularly in regions with heterogeneous hydrogeological settings or limited data availability. By refining parameter ratings and leveraging fuzzy logic's ability to manage imprecise and ambiguous information, the enhanced model provides a more reliable basis for decision-making in groundwater management and protection (Iqbal et al., 2015; Saranya and Saravanan, 2021).

2.3.3 Applications and case studies

The integration of fuzzy logic techniques with the DRASTIC method has been applied in various hydrogeological settings, demonstrating significant improvements in the accuracy and specificity of groundwater vulnerability assessments. Afshar et al., (2007) used fuzzy logic (FL) techniques to enhance the specificity of DRASTIC index in groundwater vulnerability assessment. Using a pseudo-trapezoidal MF in conjunction with Mamdani inference and center-of-gravity defuzzification, they effectively categorized each parameter into three linguistic terms and defined eight linguistic terms for a normalized DRASTIC index, thereby refining the model's ability to interpret and classify groundwater vulnerability data. Similarly, Nourani et al. (2023) advanced the DRASTIC model by integrating it with a Mamdani fuzzy logic (MFL) approach to reduce uncertainties in groundwater vulnerability assessments. This study applied MFL combined with data mining to address the inherent weaknesses of traditional DRASTIC method, especially the subjective rating of parameters. In their assessment of the Ardabil and Qorveh-Dehgolan plains, the authors found that the MFL model yielded higher accuracy in vulnerability predictions, as indicated by improved Heidke skill scores (HSS) and total accuracy (TA) values compared to the standard DRASTIC approach. The study demonstrated that even with reduced parameter inputs, the MFL model could reliably predict groundwater vulnerability, thus offering an efficient and flexible alternative for aquifers in complex hydrogeological settings. Furthermore, Iqbal et al. (2015) applied a hierarchical fuzzy system (HFS) model to address the limitation of DRASTIC method, in managing uncertainties inherent in hydrogeological data. The HFS model incorporates standard DRASTIC parameters within a fuzzy logic framework. In their assessment of Ranchi District, India, the authors found that the HFS model yielded higher accuracy in vulnerability predictions, as indicated by stronger correlation ($R^2 = 0.621$) with observed nitrate concentration data compared to the traditional DRASTIC model ($R^2 = 0.481$). The study highlights the HFS model's capacity to better represent groundwater contamination risks. Another notable application by Saranya and Saravanan, (2021) refined groundwater vulnerability assessment by developing a hierarchical fuzzy inference model (HFIM) and applying it in Cuddalore District, India. The HFIM incorporated standard DRASTIC parameters within a GIS framework, enhancing adaptability and responsiveness to data changes. Comparison with the traditional DRASTIC model showed the HFIM's superior performance, classifying vulnerability into seven nuanced categories, as opposed to DRASTIC's five. Model validation using nitrate concentration data from 40 sampling points revealed a stronger correlation in the HFIM ($R^2 = 0.704$) versus DRASTIC ($R^2 = 0.60$), with the HFIM displaying a smoother transition across vulnerability categories. This approach demonstrated that hierarchical fuzzy inference enhances vulnerability mapping precision, providing a robust tool for sustainable groundwater management in agriculturally intensive regions.

2. 4 Role of Geographic Information Systems (GIS) in vulnerability assessment

The advent of Geographic Information Systems (GIS) has markedly enhanced the methodology for creating groundwater vulnerability maps. Since the development of GIS technology in the 1990s (Esri, n.d.), it has enabled the implementation of qualitative methods within its framework and can easily perform map overlaying and indexing operations in the spatial domain (Kaur and Rosin, 2009). Merchant, (1994) was the first that applied this technology for DRASTIC implementation, and has since been widely adopted due to its robust capabilities in retrieving, storing, managing, analyzing, and visualizing geospatial data (Hasan et al., 2019; Jha and Peiffer, 2006; Koon et al., 2023; Oroji, 2018). In practice, GIS combines multiple spatial data layers, each representing critical variables influencing groundwater vulnerability, (e.g., soil type, aquifer media, and recharge rate) (See Fig. 4).

Each feature/layer is assigned a weight relative to the other in order of their impact on vulnerability and integrated to produce comprehensive vulnerability maps through GIS's sophisticated overlay and indexing techniques (Goyal et al., 2021). This process is particularly important in the application of vulnerability assessment models like DRASTIC, GOD, and SI, which rely heavily on the spatial distribution of parameters to calculate an accurate vulnerability index (Machiwal et al., 2018). Moreover, numerous case studies across various geographical regions have underscored the utility of GIS in refining the assessment process, providing a clearer, more actionable output for groundwater management (refer to Table 1 for examples). However, despite its effectiveness, the application of GIS is not without challenges. The process of data entry is time-consuming and costly, requiring all data to be digitized and accurately modeled for terrain analysis, which can be complex and technically demanding. Additionally, constraints such as data availability, resolution, and the overall cost of GIS technology can restrict its use, especially in settings with limited resources (Banerjee et al., 2023; Goyal et al., 2021).

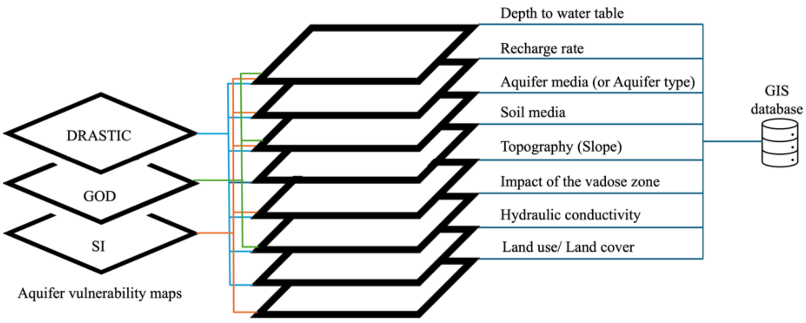


Figure 4. *Conceptual flowchart illustrating the integration of thematic layers within a GIS framework to construct groundwater vulnerability maps using DRASTIC, GOD, and SI methods.*

CHAPTER 3: METHODOLOGY

This chapter presents a detailed methodology used to assess shallow groundwater vulnerability in Southeast Hungary, starting with a description of the study area's geographical, hydrological, and socio-economic characteristics. It examines the applied assessment methods: the DRASTIC, GOD, Susceptibility Index (SI), and a pioneering Fuzzy-enhanced DRASTIC models. To validate the effectiveness of each model, the chapter employs a robust statistical validation approach using both Pearson and Spearman's rho correlations, conducted using SPSS (Statistical Package for the Social Sciences) software. This dual correlation approach ensures a thorough evaluation of the models' accuracy in predicting groundwater vulnerability. After detailing the validation process, single-parameter sensitivity analysis (SPSA) is conducted to investigate the influence of individual parameters on the vulnerability assessments, thereby enhancing the understanding of model sensitivity and robustness. Additionally, the chapter outlines the data collection strategies and sources. This structured approach ensures a comprehensive evaluation of groundwater vulnerability, aligning with the thesis's overarching goal of providing a scientifically rigorous and practically applicable framework for sustainable groundwater management in Southeast Hungary. To ensure consistency and reproducibility of spatial analyses, all thematic layers, vulnerability indices, and sensitivity analyses in this study were prepared and processed using ArcGIS 10.6.1.

3. 1 Study area description

3.1.1 Geographical characteristics

The area featured in this study located at coordinates 46°20′–47°00′ N and 20°00′–21°00′ E (Fig. 5), is part of the Great Hungarian Plain (Alföld), Hungary, within the Carpathian Basin, East-Central Europe (19.38°–22.86° E and 46.18°–48.32° N). Covering an area of 8,690 km², the region is characterized by a predominantly flat, fertile plain with an average elevation of approximately 100 meters above Baltic Sea level (MASL). The topography, generally under 2%, significantly influences surface water flow and land use, particularly agricultural practices that dominate the region's economy.

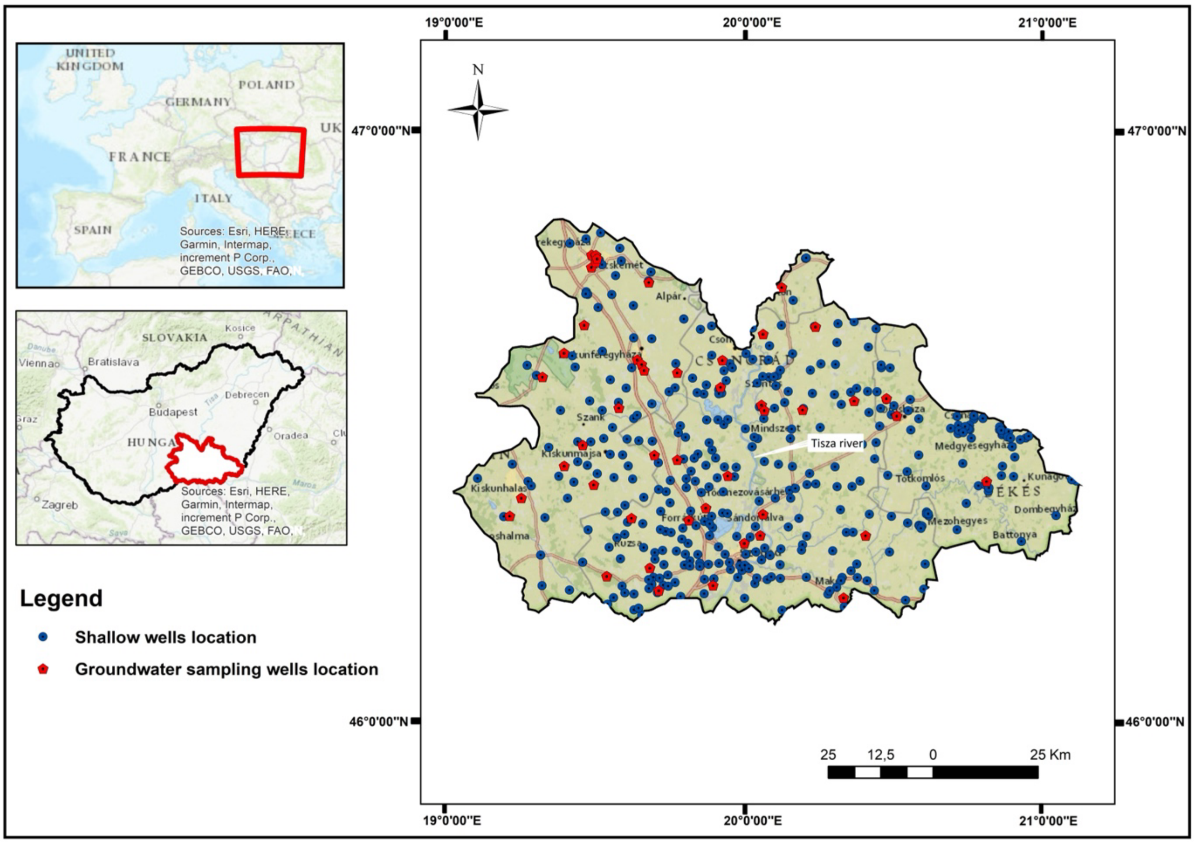


***Figure 5**. Location of the study area*

3.1.2 Hydrological and soil characteristics

The climate of the region is characterized as arid continental, heavily influenced by both dry continental and mediterranean air masses, resulting in marked temperature extremes and notably limited precipitation. Specifically, the region lies near the threshold of sub-humid conditions (*Climate - HungaroMet*, n.d.). The average annual temperatures, long-term data from 1991 to 2020 indicate that plain areas of Southeast Hungary average between 10.5 °C and 11.5 °C, with some localized zones near the southern border occasionally exceeding 11.5 °C

(*Temperature - HungaroMet*, n.d.). In addition, the region is among the driest parts of Hungary, with mean annual precipitation ranging from 500 to 550 mm (*Precipitation - HungaroMet*, n.d.). The Tisza River, Hungary's second major river (ICPDR—International Commission for the Protection of the Danube River, 2011), bisects the study region and delineates two distinctly different soil types: loose sandy soils and variable soils with finer texture. Along the riverbanks, the predominant soil types are clay and clay loam, which have low permeability, resulting in minimal infiltration. To the west of the Tisza River, the terrain is primarily sandy, interspersed with occasional areas of sandy loam, and a smaller region to the northwest is dominated by loam soils. The study area's southeast section is largely composed of loam, interspersed with patches of clay loam (European Soils Bureau Network, 2005; Farsang et al., 2017).

3.1.3 Socio-economic characteristics

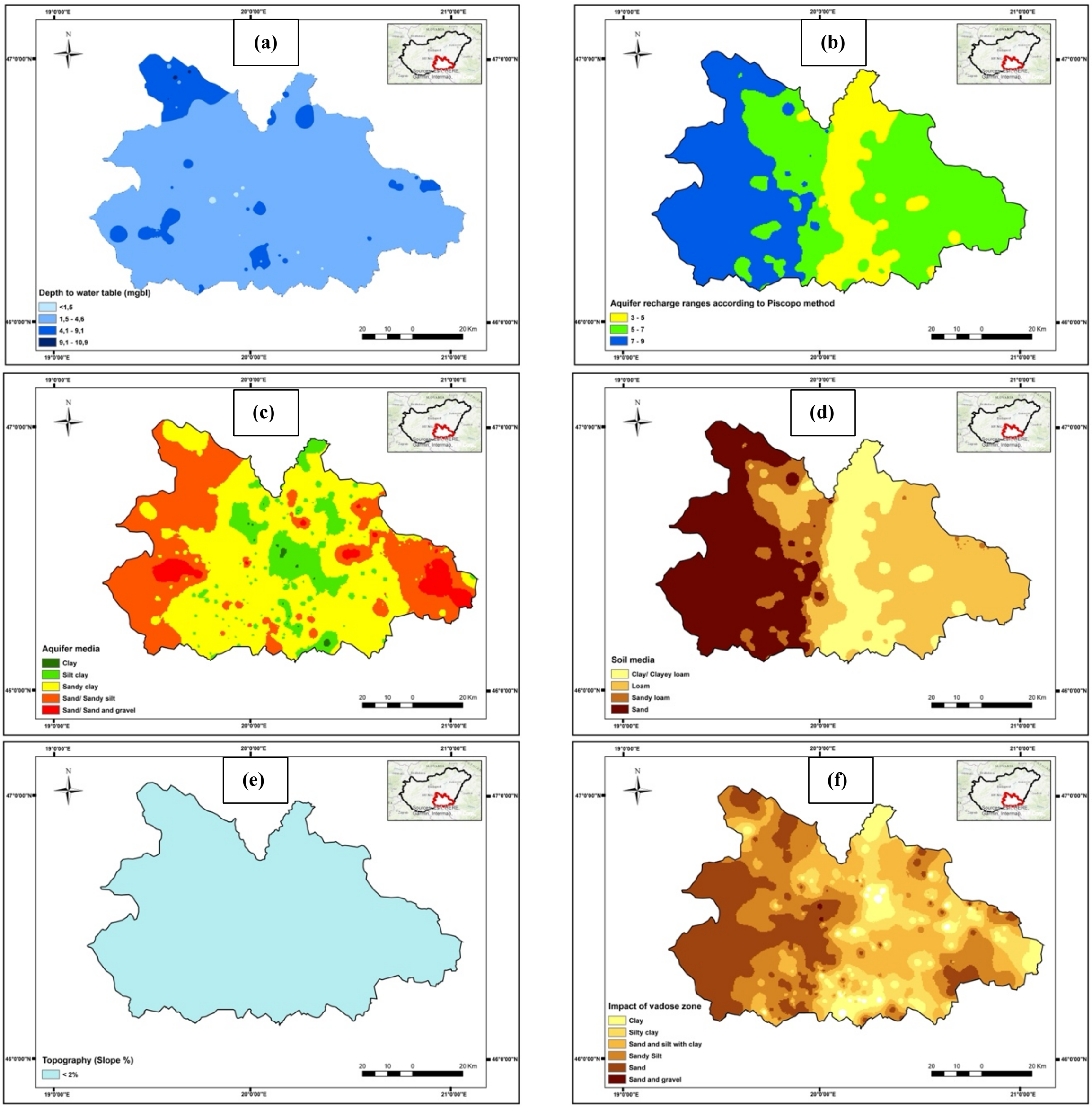
The study area has a population of approximately 708,000 people, the area spans several counties, including Csongrád-Csanád, parts of Békés, and Bács-Kiskun Counties (Hungarian Central Statistical Office, n.d.). Agriculture forms the economic backbone of this region, with over 65% of the land devoted to the cultivation of maize, sunflower, wheat, onions, and fruits (Hungarian Central Statistical Office, 2020), the first three crops are dominant on loessy areas while fruits and vegetables are typical on sand. These crops rely heavily on groundwater for irrigation, consuming approximately 4.9 million m^3 of groundwater annually (*Lower Tisza Region Water Management Directorate*, n.d.). The intensive use of fertilizers and pesticides associated with these agricultural activities significantly increases the risk of groundwater contamination, highlighting the critical need for effective water management and contamination mitigation strategies (Barreto et al., 2017; Pinke et al., 2020).

3.1.4 Environmental and pollution considerations

Given its status as one of Hungary's most productive agricultural regions and its critical role in national food production (Pinke et al., 2020), the selected study area exemplifies the challenges of balancing agricultural productivity with sustainable water management. This region is notably prone to severe, prolonged droughts, which exacerbate groundwater depletion and significantly affect groundwater table dynamics, influencing both the quantity and quality of groundwater (Rossi et al., 2023; Szöllősi-Nagy, 2022). The prevalence of agricultural practices, particularly the extensive use of nitrogenous fertilizers, contributes to elevated nitrate levels in groundwater, posing serious risks to water quality (Zhou et al., 2015). Therefore, assessing the vulnerability of aquifers to contamination is crucial for enabling policymakers to implement targeted management measures. These measures aim not only to mitigate risks of groundwater contamination but also to address the socio-economic demands of the region, ensuring a balanced approach to environmental sustainability and agricultural efficiency (Haidery et al., 2023).

3. 2 Preparation of thematic layers

In this study, the assessment of groundwater vulnerability based on different combinations of the eight parameters listed in Table 2. These parameters and their application in this study are briefly described below, and their spatial distributions are presented in Fig. 6.



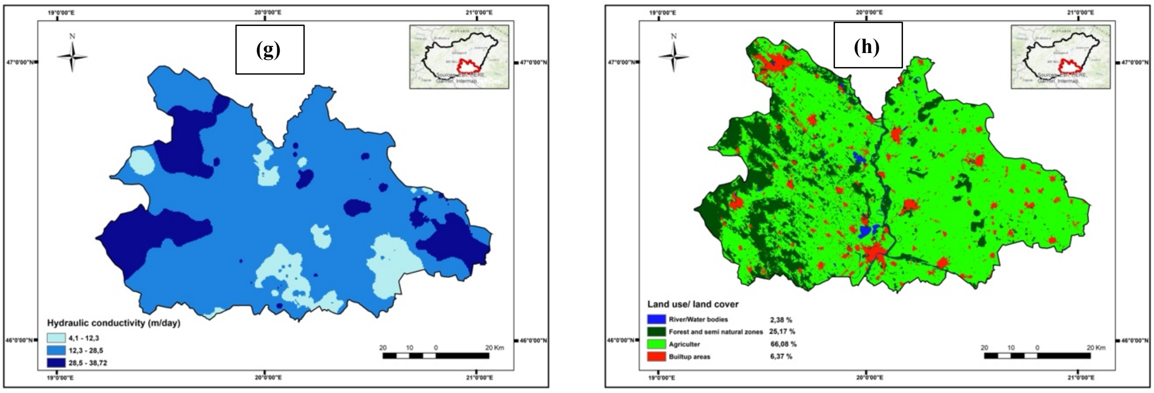


Figure 6. *Spatial distributions of parameters describing the groundwater vulnerability to contamination in the study area: (a) depth to water table (mbgl), (b) recharge rate (Piscopo method), (c) aquifer media, (d) soil media, (e) topography (slope%), (f) vadose zone, (g) hydraulic conductivity (m/day), and (h) land use.*

3.2.1 Depth to the water table

The depth to the water table (D) controls the leaching process and defines the distance/time required for dissolved contaminants to move between the upper edge of the soil and upper edge of the aquifer (Kirlas et al., 2022). Shallow aquifers with water tables near the surface are highly vulnerable to contamination by diffusion, which can be attributed to the lower potential for natural attenuation. The depth to the water table was measured at 383 shallow wells in spring 2022 (Fig. 5), revealing depths ranging from 1.1 to 10.9 meters below ground level, and the observed data were interpolated by kriging and assigned a rating of 5–10 based on its impact on the vulnerability of the local area (Table 5), the weighting factors of the D parameter are provided in Table 2. This spatial distribution is visually represented in Figure 6a, illustrating the depth variations across the study area and aiding in the assessment of contamination risks.

3.2.2 Aquifer recharge rate

The aquifer recharge rate (R) refers to the annual volume of water that directly infiltrates the shallow aquifer, and it is the main pathway for contaminant transport. Because of the unavailability of data on recharge rates in the study area, the recharge rates were estimated by applying the Piscopo method (Piscopo, 2001), which integrates factors for the land slope, rainfall, and soil permeability, as shown in Eq. (1) (Asghari Moghaddam et al., 2023; Kirlas et al., 2022; Yankey et al., 2021):

Net recharge index (Ri) = land slope factor (%) + rainfall factor (mm) + soil permeability factor (1)

Saravanan et al., (2020) demonstrated the effectiveness of this method by comparing four different approaches to estimate the net recharge rate and assessing their suitability for evaluating groundwater vulnerability in the Upper Palar River basin, Tamil Nadu, India, using the DRASTIC model. They found the Piscopo method to be very effective at calculating the recharge rate, and it showed a good correlation with the observed NO_3^- concentration.

For this study, the land slope factor (%) was determined using Advanced Spaceborne Thermal Emission and Reflection Radiometer digital elevation model (ASTER-DEM) data in raster file format with a spatial resolution of 5m × 5m. The data showed that approximately 99.9% of the study area had a slope of less than 2%, leading to a uniform slope factor rating of 4 (Table 4). The rainfall factor was calculated at nine precipitation stations in the study area, and it was estimated at around 326 mm/year in 2021. Consequently, a fixed rating of 1 was assigned. The soil permeability factor was obtained using the results of a soil survey (0–40 cm depth) conducted within the study area (Farsang et al., 2017). The soil permeability was classified according to the USDA system (1994). The soil of the study area mainly comprised clay and clay loam along the eastern side of Tisza River (very low to low permeability), sandy loam to sand on the western side (moderate to high permeability), and loam in the southeast and small parts of the northwest (moderate permeability). Table 4 lists the ratings of the recharge rate, which mainly depended on the soil permeability in this study. The aquifer recharge ratings layer is visually mapped out in Figure 6b.

Table 4. *Ratings of the recharge rate according to the Piscopo method (Piscopo, 2001)*

Slope (%)		Rainfall (mm/year)		Soil permeability		Recharge rate	
Range	Rating	Range	Rating	Range	Rating	Range	Rating
< 2	4	< 500	1	High	5	11 - 13	10
2 – 10	3	500 - 700	2	Mod-high	4	9 - 11	8
10 – 33	2	700 - 850	3	Moderate	3	7 - 9	5
> 33	1	> 850	4	Slow	2	5 - 7	3
				Very slow	1	3 - 5	1

3.2.3 Aquifer media

The aquifer media (*A*) characterizes the physical and hydraulic properties of the saturated zone, which controls the contaminant attenuation process (Rama et al., 2022). In this study, aquifer media were assessed by analyzing the lithological profiles from 383 wells within the study area. This analysis identified the main components of the aquifer media including fine to medium-grained sand, sandy clay, clay, and sandy silts. Based on their potential to attenuate contaminants, these media types were classified into five categories. Each category was assigned a rating ranging from 4 to 8, as detailed in Table 5. These scores reflect the varying degrees of permeability and contaminant filtration capacity, where higher scores indicate materials with greater permeability that potentially allow for faster contaminant migration. The aquifer media layer is detailed in Figure 6c.

Table 5. *Ranges of values and ratings of the parameters used by the three index-overlay methods to calculate their vulnerability indices (Aller et al., 1987; S. Foster, 1987; Ribeiro, L., 2000). (mbgl: meters below ground level)*

Parameters	Attributes	Attribute values					
Depth to groundwater table (mbgl*)	Range	< 1.5	1.5 - 4.6	4.6 - 9.1	9.1 - 15.2	> 15.2	
	Rating for DRASTIC	10	9	7	5	3	
	Rating for GOD	1.0	0.9	0.8	0.7	0.6	
Aquifer media (for DRASTIC)	Types	Basalt	Sand & gravel	Massive sandstone	Metamorphic/ igneous		
	Rating	9	8	6	4		
Aquifer type (for GOD)	Types	Sand & gravel	Silty & clay	Clay			
	Rating	0.7	0.5	0.4			
Soil media	Types	Sand	Sandy loam	Loam	Clay loam		
	Rating	9	6	5	3		
Topography (slope, %)	Range	< 2%	2 - 6	6 - 12	12 - 18	> 18	
	Rating	10	9	5	3	1	
Impact of vadose zone	Types	Sand & gravel	Sandy silt	Silty clay	Clay		
	Rating	8	7	6	3		
Hydraulic conductivity (m/day)	Range	> 81.5	40.8 - 81.5	28.5 - 40.8	12.3 - 28.5	4.1 - 12.3	0.04 - 4.1
	Rating	10	8	6	4	2	1
Land use/cover	Types	Agriculture	Built-up	Forests & semi-natural zones	River/ water bodies	Shrub & grassland	
	Rating	90	70	0	0	50	

3.2.4 Soil media

The soil media (S) refers to the upper layer of the vadose zone, which is characterized by biological activities (e.g., microbial activity, organic matter, presence of roots) and contact with the atmosphere. It represents the initial medium that transfers the contaminant beneath Earth's surface. Data on the soil media were extracted from a recent comprehensive report on soil conditions and irrigation possibilities in the local catchment area (Farsang et al., 2017). The soil types were mainly loam in the eastern part of the study area, and sand/sandy loam on the western side of Tisza River. Clay/clay loam covered about one-sixth of the study area and was mostly distributed along the riverbanks with small patches to the south. For the purpose of vulnerability assessment, these soil types were categorized into four classes based on their infiltration capacities, with ratings assigned from 3 to 9. These ratings indicate the degree to which each soil type either facilitates or restricts water and contaminant movement, with higher values suggesting greater permeability and lower resistance to infiltration (Table 5). The spatial distribution of these soil types is visually detailed in Figure 6d, aiding in the comprehensive understanding of their implications for groundwater vulnerability.

3.2.5 Topography

The topography (T), or slope, represents the impact of the land surface on the leaching mechanism. In general, the rate of runoff is controlled by the local topography, which affects the probability of a contaminant being transported or retained on ground that it can infiltrate (Rama et al., 2022). Consequently, the topography represents a qualitative indication of the runoff/infiltration ratio as a function of the terrain conditions. For this assessment, topography was derived from DEM and was converted into slopes by using the 3D Analyst tool based on ArcGIS 10.6.1. The resulting slopes across most of the study area (approximately 99.9%) were between 0 and 2% and reached 4% in a narrow zone toward the south, which was close to the border with Serbia. Despite this variation, the slopes were uniformly classified into a single category and assigned the highest vulnerability rating of 10. This categorization was based on the understanding that even slight inclines could significantly affect runoff dynamics in flat terrains. The rationale behind the ratings is detailed in Table 5, with the weighting factors provided in Table 2.

3.2.6 Vadose zone

The vadose zone provides a pathway for contaminants from the land surface to reach the capillary fringe zone. It can be used to estimate the mitigation potential of the unsaturated layer between the soil cover and groundwater table (i.e., capillary fringe) (Jain, 2023). This zone was determined from lithological data collected at 383 wells, as depicted in Figure 5. Based on this data, the vadose zone was categorized into five classes: sand and gravel/sand, sand and silt with clay, silty clay and clay. These classifications reflect varying levels of permeability and contaminant transmission potential, with ratings assigned of 3–8 according to the transmissibility of contaminants to the aquifer, as detailed in Table 5. The corresponding weighting factors are listed in Table 2. Spatially, sand predominantly covers the western part of the study area and parts of the southeast, while clay is more concentrated around the middle and southern parts of Szeged town. Silt and clay mixtures are found throughout the rest of the study area, indicating a diverse range of vadose zone compositions that influence groundwater vulnerability.

3.2.7 Hydraulic conductivity

The saturated hydraulic conductivity (*K*) refers to the capacity of an aquifer to transmit water based on the horizontal hydraulic conductivity of the saturated zone (K_s) (Darcy, 1856). Under the assumption that a contaminant mimics the mobility of groundwater (Aller et al., 1987), this parameter represents the migration of contaminants from the point of infiltration. In this study, hydraulic conductivity layer was estimated using the empirical Beyer equation (1964) (Eq. 2), which calculates conductivity based on the particle size distribution of aquifer sediments, such as the graphical standard deviation and cumulative weight percentage (Wang et al., 2017):

$$K = Cb \times \frac{g}{V} \times \log\left(\frac{500}{Cu}\right) \times d_{10}^{2} \qquad (2)$$

where V is the kinematic viscosity, g is the acceleration due to gravity, $Cb = 6 \times 10^{-4}$ (dimensionless), and Cu is the coefficient of uniformity (dimensionless), which is defined as the ratio of the grain sizes at 60% passing and 10% passing ($Cu = d_{60}/d_{10}$).

The hydraulic conductivity values were spatially interpolated using kriging in ArcGIS 10.6.1. The average hydraulic conductivity of the study area was estimated at 4.18–38.72 m/day. Based on these values, three classes were established and assigned ratings from 1 to 6 to indicate varying degrees of water transmission potential (Table 5). The weighting for hydraulic conductivity, reflecting its relative importance in the vulnerability assessment, is detailed in Table 2.

3.2.8 Land use/cover

The land use and cover significantly inform the assessment of groundwater vulnerability by indicating the types of natural and anthropogenic activities occurring at the surface (e.g., agriculture, artificial development, natural areas), which profoundly impact groundwater quality (Nguyen and Tat, 2024). In this study, land use/cover categories were broadly classified into agriculture, rivers/water bodies, built-up areas, forests, and semi-natural areas. Each category was meticulously assigned a vulnerability rating based on its potential impact on groundwater contamination, as detailed in Table 5. For instance, agricultural activities, including irrigated perimeters and permanent crops, which constitute about 66% of the study area, were assigned a high rating of 90 due to their significant potential to introduce contaminants into the groundwater system. Conversely, forests and semi-natural areas, along with water bodies, generally presumed to exert minimal contamination risk, received a minimal rating of 0. Built-up areas, making up approximately 6% of the landscape, were rated at 75, reflecting their moderate impact relative to agricultural zones. The weighting for LU/LC parameter, reflecting its relative importance in the vulnerability assessment, is detailed in Table 5.

3. 3 Methodologies for groundwater vulnerability assessment

Figure 7 illustrates the workflow used to evaluate the selected methodologies for groundwater vulnerability assessment, including the standard DRASTIC, GOD, SI, and Fuzzy-enhanced DRASTIC model. These methods are recognized for their qualitative efficiency in assessing groundwater vulnerability that are cost-effective and time-efficient (Elmeknassi et al., 2021; Machiwal et al., 2018). As discussed in Chapter 2, each method represents a different approach to assessing vulnerability—ranging from the intrinsic, parameter-weighted frameworks of DRASTIC and SI, to the simplified parametric classification of the GOD method, and finally to the advanced Fuzzy-enhanced DRASTIC model, which addresses uncertainties associated with conventional rating systems. The selected models rely on the spatial integration of multiple thematic layers and the subjective assignment of weights and ratings based on hydrogeological significance. Table 2 summarizes the parameters and their associated weights used in each method, while Table 5 presents the ranges of the ratings applied during the calculation of the vulnerability indices. ArcGIS Spatial Analyst was used to process and analyze spatial data for all methods. Both inverse distance weighting (IDW) and Kriging interpolation were tested to determine which provided the better accuracy. Kriging demonstrated the lowest Root Mean Square Error (RMSE) was selected for the remainder of the study, ensuring optimal accuracy in our spatial analyze.

To evaluate the predictive effectiveness of each model, the vulnerability indices generated by the four methodologies were validated against measured concentrations of nitrate (NO_3^-) from 46 monitoring wells across the study area. Pearson's and Spearman's correlation coefficients were computed to quantify the strength and direction of the relationship between the vulnerability scores and observed nitrate levels, thereby determining each model's reliability in identifying areas at risk of contamination. Additionally, this study incorporated Single-Parameter Sensitivity Analysis (SPSA) for the DRASTIC, SI, and Fuzzy-enhanced DRASTIC models to identify the most influential parameters affecting the vulnerability index. SPSA quantifies the contribution of each parameter by calculating its effective weight, which is derived from its rated value, assigned weight, and the total vulnerability index. This analysis enables a deeper understanding of the internal structure of each model and highlights how spatial variability in specific parameters influences final vulnerability scores.

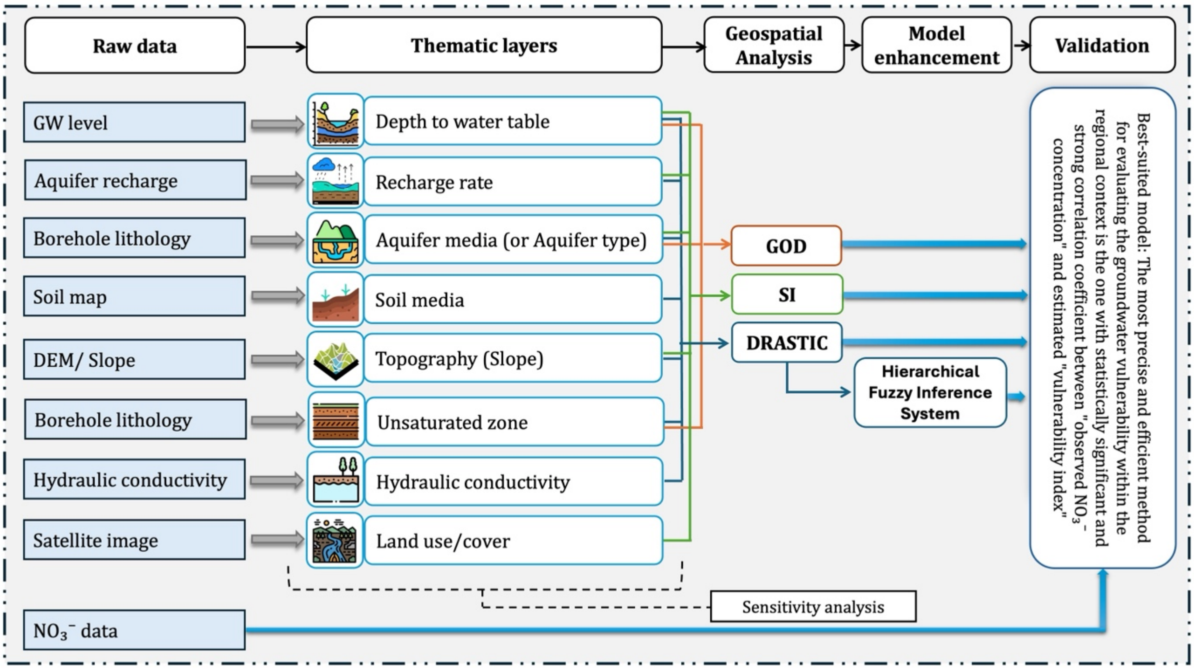


Figure 7. *Methodological workflow for groundwater vulnerability analysis*

3.3.1 DRASTIC method

DRASTIC, a systematic approach developed by the United States Environmental Protection Agency (Aller et al., 1987), assesses groundwater vulnerability through a rating and weighting system. Recognized for its cost-effectiveness, simplicity, and reliance on readily available data, DRASTIC is extensively utilized in groundwater vulnerability studies (Haidery et al., 2023). This method involves the integration of seven critical hydrogeological factors that are considered intrinsic to the sensitivity of an aquifer to potential contaminants from the ground surface (Rama et al., 2022). These thematic layers or factors include: Depth to water table (D), aquifer Recharge (R), Aquifer type (A), Soil media (S), Topography (slope) (T), Impact of the vadose zone (I), and Hydraulic Conductivity (C) of the aquifer. The final DRASTIC vulnerability index (Vi) for each pixel or unit grid cell within the study area is computed using a weighted linear combination of these parameters, represented by the equation detailed in the Table 1. Table 2 delineates both the parameters and their respective weights for computing the

DRASTIC index. After calculating the vulnerability index (Vi), areas are identified as more sensitive to groundwater contamination compared with others. The range of DRASTIC scores extends from 23, indicating the least vulnerability, to 226, indicating the highest potential for vulnerability. Corniello et al., (1997) have further categorized these scores into distinct classes ranging from very low to very high vulnerability potential, as outlined in Table 6.

Table 6. *Criteria used by the three index-overlay methods to assess their vulnerability indices*

Vulnerability degree		Very low	Low	Moderate	High	Very high	Reference
Vulnerability index	DRASTIC	< 80	80 – 120	121 - 160	161 – 200	> 200	(Corniello et al., 1997)
	GOD	0 – 0.1	0.1 – 0.3	0.3 – 0.5	0.5 – 0.7	0.7 – 1	(Foster, 1987)
	SI	-	< 45	45 - 64	65 - 85	> 85	(Ribeiro, L., 2000)

3.3.2 GOD method

In this study, the GOD method is employed to assess groundwater vulnerability in Southeast Hungary, utilizing its straightforward framework developed in England by Foster, (1987). This method assesses groundwater vulnerability by examining three key parameters: Groundwater occurrence (G), which categorizes the type of aquifer based on the degree of confinement; the Overlying lithological characteristics (O), referring to the properties of the vadose zone; and the Depth to the groundwater table (D). Each of these parameters is rated on a scale from zero (indicating no vulnerability) to one (indicating high vulnerability), reflecting their inherent characteristics to shield against or permit contaminant penetration. No weighting is applied to the parameters, as they are considered to have equal influence on aquifer vulnerability. The GOD vulnerability index (I_{vGOD}) is then calculated by multiplying the ratings of these three parameters, as detailed in Table 5. I_{vGOD} is then used to classify the vulnerability according to the criteria defined in Table 6.

3.3.3 Susceptibility Index (SI)

In Portugal, Ribeiro, (2000) introduced the SI as a specialized approach to assess groundwater vulnerability to vertical agricultural contamination, particularly with regard to nitrate and pesticides, is applied within the Southeast Hungary context to address the significant impacts of agricultural activities. The SI method considers five parameters, as detailed in Table 2, and it is a modified version of DRASTIC. Four parameters are identical to those used in DRASTIC, and they are assigned ratings across a range 10 times larger than that used by DRASTIC. The fifth parameter is the land use/cover (LU/LC), allows for integrating the impact of anthropogenic activities in its calculation, thus transitioning the assessment from intrinsic to specific vulnerability (Ghouili et al., 2021; Ribeiro et al., 2017). Land use is rated according to the classification provided by Ribeiro as shown in Table 5. Then, weighting factors are assigned to each parameter are listed in Table 2, and the SI vulnerability index (Iv_{SI}) is computed by linearly combining the scores and weights of the five parameters represented by the equation detailed in the Table 1. I_{vSI} is then used to classify the vulnerability into one of four classes according to the criteria defined in Table 6.

3.3.4 Fuzzy-enhanced DRASTIC approach

In addressing the inherent limitations and uncertainties of traditional groundwater vulnerability assessments, this study advances the integration of a hierarchical fuzzy inference system (FIS) with the established DRASTIC model, thus creating a Fuzzy-enhanced DRASTIC model. This approach utilizes fuzzy membership functions for each of the DRASTIC parameters—Depth to water table (D), Net recharge (R), Aquifer media (A), Soil media (S), Topography (T), Impact of the vadose zone (I), and Hydraulic conductivity (C)—to provide a more nuanced representation of each parameter's contribution to groundwater vulnerability. These functions facilitate the handling of overlapping data ranges and the subjective nature of environmental assessments, allowing for a more accurate and flexible evaluation. Figure 8 presents a detailed flowchart of the proposed methodology, systematically outlining each step from data compilation to the final vulnerability mapping. Each of these steps is further elaborated in subsequent subsections, ensuring a comprehensive understanding of the methodology's application.

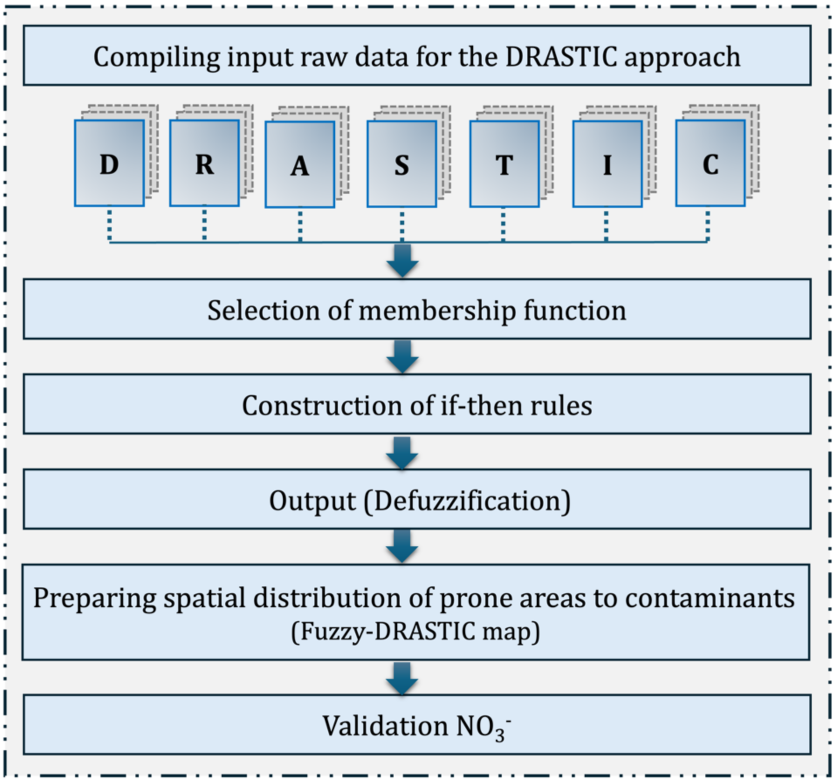


***Figure 8**. Flowchart of the Fuzzy-enhanced DRASTIC methodology for groundwater vulnerability assessment*

3.3.4.1 Hierarchical fuzzy inference system (FIS)

In this study, the DRASTIC model is enhanced through the integration of a hierarchical fuzzy inference system (FIS), addressing the limitations of static parameter ratings inherent in traditional approache. This methodology employs a multi-level fuzzy inference system, depicted in Figure 9, that processes inputs through a series of interconnected layers. This structured approach substantially reduces the rule base size and computational demands, the hierarchical FIS offers a more efficient and scalable alternative to single-layer fuzzy systems, making it particularly suitable for groundwater vulnerability assessments in data-scarce or complex hydrogeological settings (Gesim & Okazaki, 2018; Nobre et al., 2007; Rezaei et al., 2013; Saranya & Saravanan, 2022). The hierarchical structure organizes the DRASTIC parameters into six fuzzy inference systems (FISs), (FIS1 through FIS6), with the output of one level serving as the input of the next. For example, the parameters depth to the water table (D) and recharge rate (R) are combined to establish the first level of the hierarchy. The results of this level are then integrated with the aquifer media (A) parameter to form the second level, and this process continues sequentially.

In the application of this refined methodology, MATLAB R 2019 is utilized to develop the FIS. During fuzzification parametric values are converted into linguistic variables and assigns them trapezoidal membership functions MFs (Fig. 10), this function is chosen for its simplicity and computational efficiency, which contribute to its reliability in capturing parameter variability (Iqbal et al., 2015). Defined by four parameters that describe its shape— a, b, c, and d—the trapezoidal MF allows for nuanced representation of parameter ranges, as shown in Eq. (3). Table 7 presents the parameters and their corresponding MFs. This table provides accurate values across a diverse array of parameter subcategories, ensuring simplicity and convenience. This format is appropriate for managing multiple input points effectively.

$$\mu \mathrm{A}(x) = \begin{cases} 0, (x < a) \; or \; (x > d) \\ \frac{x-a}{b-a}, (a \leq x \leq b) \\ 1, (b \leq x \leq c) \\ \frac{d-x}{d-c}, (c \leq x \leq d) \end{cases} \quad (3)$$

Where:

- a: The starting point of the trapezoid where the membership value starts to increase from 0.
- b: The point where the membership function reaches a value of 1, starting the flat "top" of the trapezoid.
- c: The point where the flat "top" of the trapezoid ends, and the membership value starts to decrease.
- d: The ending point of the trapezoid where the membership function value returns to 0.

For $x < a$ or $x > d$: The membership value $\alpha(x) = 0$, indicating that x is outside the trapezoid.

For $a \leq x \leq b$: The membership value increases linearly from 0 to 1 as x moves from a to b.

For $b \leq x \leq c$: The membership value $\alpha(x) = 1$, indicating the plateau or "top" of the trapezoid, where x is fully in the fuzzy set.

For $c \leq x \leq d$: The membership value decreases linearly from 1 to 0 as x moves from c to d.

The following phase entails constructing the conditional segment by establishing a rule that links the input parameters with the outputs analyzed by the inference engine. MATLAB supports two types of inference engines: Mamdani and Sugeno. The Mamdani inference engine is selected in this study due to its superior capability to handle human inputs and its highly interpretable results (Selvaraj et al., 2020). This engine operates on IF–THEN rules, integrating OR/AND operators to connect the input and output parameters. The final step in this process is translating the fuzzy output values back into precise real-world values.

The subsequent sections detail the operational hierarchy of the FIS, demonstrate the integration of the hydrogeological parameters (from the depth to the water table to hydraulic conductivity), ultimately assessing the vulnerability of groundwater in specific districts. This hierarchical FL approach presents a sophisticated framework designed to enhance the accuracy and applicability of groundwater vulnerability assessment

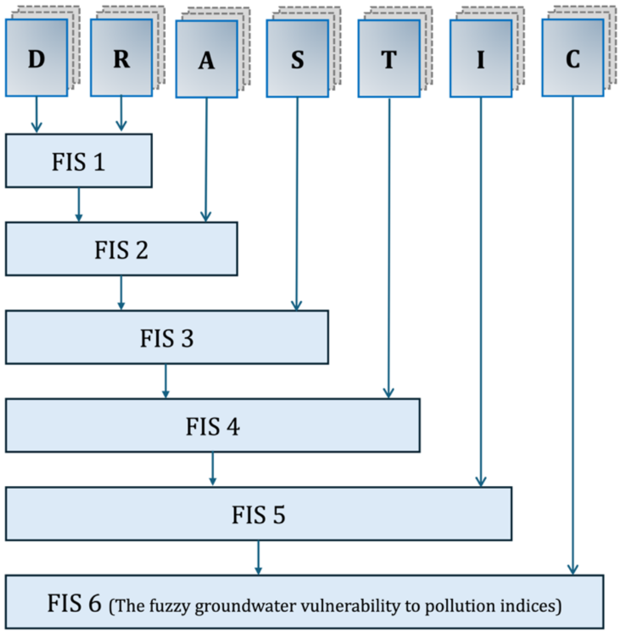


Figure 9. *Structure of hierarchical FL model for prediction of groundwater vulnerability to potential pollution*

i. *FIS1: Groundwater depth vs. Recharge rate*

The initial component of our hierarchical FIS, FIS1, evaluates the relationship between groundwater depth (D) and aquifer recharge (R), two critical hydrogeological parameters that significantly influence groundwater vulnerability to contamination. In the spring of 2022, water-table depths measured at 383 well locations (Fig. 5), were interpolated using the kriging method in ArcGIS 10.8, revealing depths of 1.1–10.9 m below ground level (mbgl). These values were subsequently categorized into four vulnerability ranges—low, moderate, high, and very high. Each class corresponds to a specific Membership Function (MF), represented in Table 7.

In FIS1, the aquifer recharge (R) parameter is segmented into three ranges, each defined by a distinct MF, as detailed in Table 7. This setup allows for nuanced modelling of the interaction between depth and recharge in affecting vulnerability. For the outputs of FIS1, five MFs are designed to integrate these inputs into comprehensive vulnerability assessments. The total number of operational rules for this layer is calculated by multiplying the four MFs for depth to the water table by the three MFs for aquifer recharge, yielding a total of 12 rules. These rules are comprehensively listed in Table 8, which provides a detailed framework of the operational logic for FIS1. Example rules include:

- Rule 1: If the depth to the water table is low (L) and the aquifer recharge is low (L), then the output for FIS1 is very low (VL).
- Rule 2: If the depth to the water table is low (L) and the aquifer recharge is moderate (M), then the FIS1 classification is low (L).
- …
- Rule 9: If the depth to the water table is high (H) and the aquifer recharge is high (H), then the FIS1 output is very high (VH).

Table 7. *Parameters and corresponding MFs*

DRASTIC Parameters		Fuzzy membership function	
Layers	Attribute values	Category	
Depth to groundwater table (mbgl*)	< 1.5	Very high	MF1
	1.5 - 4.6	High	MF2
	4.6 - 9.1	Moderate	MF3
	9.1 - 15.2	Low	MF4
Aquifer recharge ratings	7 - 9	High	MF1
	5 - 7	Moderate	MF2
	3 - 5	Low	MF3
Aquifer media	Sand & gravel	Very high	MF1, MF2
	Massive sandstone	High	MF3
	Metamorphic/igneous	Moderate	MF4, MF5
Soil media	Sand	Very high	MF1
	Sandy loam	High	MF2
	Loamy sand	Moderate	MF3
	Sandy clay/clay loam/sandy clay loam	Low	MF4
	Clay	Very low	MF5
Topography (slope, %)	< 2%	Very high	MF1
	2 - 6	High	MF2

Impact of vadose zone	Sand & gravel	Very high	MF1
	Sand/Sandy silt	High	MF2
	Sand and silty with clay	Moderate	MF3
	Silty Clay	Low	MF4
	Clay	Very low	MF5
Hydraulic conductivity (m/day)	> 81.5	Very high	MF1
	40.8 - 81.5	High	MF2
	28.5 - 40.8	Moderate	MF3
	12.3 - 28.5	Low	MF4
	4.1 - 12.3	Very low	MF5

** mbgl: meters below surface*

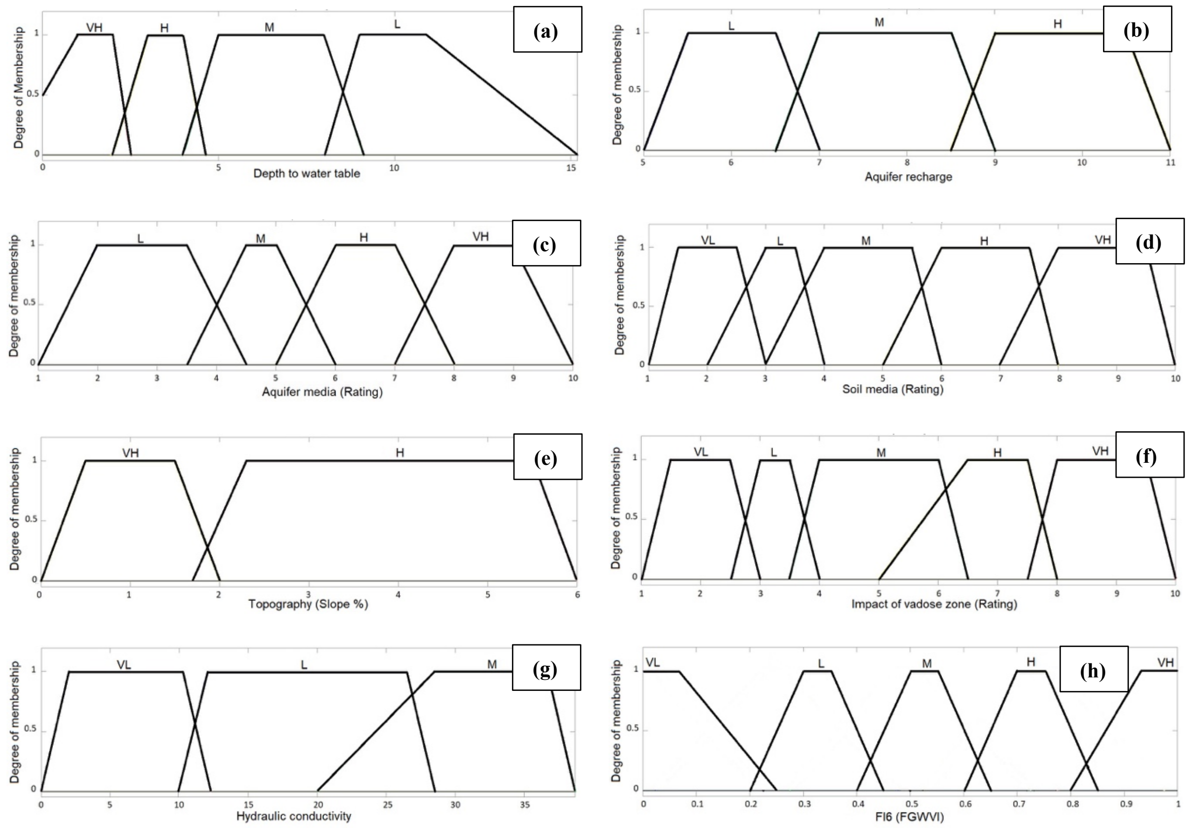


***Figure 10**. MFs of each parameter: (a) depth to water table, (b) aquifer recharge, (c) aquifer media, (d) soil media, (e) topography, (f) impact of vadose zone, (g) hydraulic conductivity, and (h) groundwater vulnerability index*

ii. FIS2: FIS1 vs. Aquifer media

In the construction of FIS2 within our hierarchical fuzzy inference system, the outputs from FIS1, characterized by five membership functions (MFs)—very low (VL), low (L), moderate (M), high (H), and very high (VH)—serve as inputs alongside the aquifer media parameter. The aquifer media parameter is classified into four MFs: low (L), moderate (M), high (H), and very high (VH). This arrangement results in a comprehensive rule base consisting of 20 unique rules, calculated as the product of the MFs from both FIS1 and aquifer media (5 × 4). These specific rules are detailed in Table 8.

The aquifer media layer is delineated based on the lithological profiles obtained from the 383 wells within the study site (Fig.2); primary components, such as fine to medium-grained sand, clay, and sandy silts, are identified (Fig. 6c). These components are transformed into quantitative fuzzy sets on a scale of 1–10, reflecting their respective influences on groundwater vulnerability. For instance, areas with sand and gravel sediments are assigned MFs of high to very high, whereas semi-consolidated sediments are classified as moderate. Silty clay/clayey sediments, associated with minimal percolation potential, are categorized with low MFs. Figure 10c illustrates the MFs applied to the aquifer media, providing a visual representation of this categorization.

***Table 8**. Rule bases for six FISs*

FIS1						
THEN FIS1		IF Aquifer recharge				
AND depth to water table		L	M	H		
	L	VL	L	M		
	M	L	M	H		
	H	M	M	VH		
	VH	M	H	VH		
FIS2						
THEN FIS2		IF Aquifer type				
AND FIS1		L	M	H	VH	
	VL	VL	L	M	M	
	L	VL	L	M	M	
	M	L	M	H	H	
	H	M	M	VH	VH	
	VH	M	H	VH	VH	
FIS3						
THEN FIS3		IF Soil media				
AND FIS2		VL	L	M	H	VH
	VL	VL	VL	L	M	M
	L	VL	VL	L	M	M
	M	L	L	M	H	H
	H	M	M	M	VH	VH
	VH	M	M	H	VH	VH
FIS4						

THEN FIS4		IF Topography (slope)				
AND FIS3		H	VH			
	VL	M	M			
	L	M	M			
	M	M	H			
	H	VH	VH			
	VH	VH	VH			
FIS5						
THEN FIS5		IF Impact of vadose zone				
AND FIS4		VL	L	M	H	VH
	VL	VL	VL	L	M	M
	L	VL	VL	L	M	H
	M	L	L	M	H	H
	H	M	M	H	VH	VH
	VH	M	M	H	VH	VH
FIS6						
THEN FIS6		IF Hydraulic conductivity				
AND FIS5		VL	L	M		
	VL	VL	VL	L		
	L	VL	VL	L		
	M	L	L	M		
	H	L	M	H		
	VH	M	M	H		

VL: Very Low; L: Low; M: Moderate; H: High; VH: Very High

iii. FIS3: FIS2 vs. Soil media

The FIS2 outputs are integrated with the soil media parameter to form the basis of FIS3. In preparation for FIS3, the FIS2 outputs are reclassified into five classes: VL, low (L), moderate (M), high (H), and VH. This reclassification prepares the outputs for integration with the soil media parameter, enhancing the model's sensitivity to variations in soil type. The soil media data, derived from a comprehensive report on soil conditions and irrigation potentials within the study site (Farsang et al., 2017), indicate that loam predominates in the eastern sections, while sand and sandy loam are more common on the western side of Tisza River. Clay and clay loam soils are primarily found along the eastern side of Tisza River (Fig. 6d). These soil types are transformed into a fuzzy set scale of 1–10, with MFs are assigned based on their permeability and infiltration characteristics. Figure 10d depicts the MFs assigned to each soil type, categorized into five levels corresponding to the fuzzy set classes to reflect their influence on groundwater vulnerability: VH, high (H), moderate (M), low (L), and VL. This categorization forms a comprehensive rule base of 25 unique rules, calculated as the product of the MFs from the reclassified FIS2 outputs and the soil media parameter (5 × 5). These specific rules are thoroughly detailed in Table 8.

iv. FIS4: FIS3 vs. Topography

In the development of FIS4 within our hierarchical FIS, the FIS3 outputs are integrated with the topography parameter. For this analysis, the topography of the study area is extracted from DEM data with a 5 × 5 m resolution and converted into slope percentages using the 3D Analyst tool in ArcGIS 10.6.1. The slope across of the study region varies between 0% and 2%, which encompasses approximately 99.9% of the area, while a narrow zone toward the southern part near the Serbian borders exhibited slopes up to 4%. Based on these findings, two MFs—VH and high (H)—are assigned to represent the slope classes. Figure 10e illustrates the MFs assigned to the topography parameter.

To ensure consistency with previous stages, the FIS3 outputs are reclassified into five classes: very low (VL), low (L), moderate (M), high (H), and very high (VH), aligning with the integration of topography data. This integration generates a total of 10 operational rules, detailed in Table 8, which govern the combined impact of previous hydrogeological parameters and slope on groundwater vulnerability assessment.

v. FIS5: FIS4 vs. impact of vadose zone

In the formulation of the fifth FIS (FIS5), the FIS4 outputs are integrated with the impact of the vadose zone parameter, enhancing the understanding of contaminant transport from the soil surface to the aquifer. Figure 6f presents the characterization of the vadose zone within the study area, which is determined using the lithological data collected from the 383 wells. The vadose zone materials are then assigned MFs based on their potential influence on contamination pathways: sand and gravel, which are highly permeable, are assigned a very high (VH) rating; sand/sandy silt formations are rated as high (H); mixtures of sand and silty clay are moderate (M); silty clay which typically restricts fluid movement, is rated as low (L); and clay is categorized as very low (VL). Figure 10f displays the MFs assigned to the impact of the vadose zone, with each type quantified on a scale of 1–10 based on its influence on groundwater vulnerability.

FIS5, thus, operates with two input parameters, each categorized into five MFs. The operational rules for this FIS are comprehensive and tailored to reflect the intricate interactions between the vadose zone's material characteristics and the topographic features processed in FIS4. These rules are systematically detailed in Table 8.

vi. FIS6: FIS5 vs. hydraulic conductivity

FIS6 stands as the culmination of our hierarchical fuzzy inference system, designed to deliver a comprehensive assessment of groundwater vulnerability to pollution. This final stage integrates the outputs from FIS5 with the hydraulic conductivity parameter. In the study area, hydraulic conductivity ranges from 4.18 to 38.72 m/day, as detailed in Figure 6g. These values are segmented into three distinct classes— very low, low, and moderate—each corresponding to a specific MF that reflects the varying conductivity level. These classifications are visually depicted in Figure 10g, and the Figure 10h further display the MFs utilized in FIS6, encapsulating the final input synthesis for predicting groundwater vulnerability accurately. The operational rules for FIS6, listed in Table 8, systematically combine the hydraulic conductivity membership functions (MFs) with the preceding FIS5 outputs.

By synthesizing these factors, FIS6 accurately predicts areas at greatest risk, providing essential information for effective groundwater management strategies.

3. 4 Methods validation and effectiveness assessment

3.4.1 Correlation Analysis

Validation of aquifer vulnerability assessment methodologies remains a significant challenge due to the absence of a universally standard validation approach (Hasan et al., 2019; Sayed et al., 2023). Researchers have applied different models to increase confidence in their vulnerability maps. The most common approach used to validate vulnerability maps is to compare the results of different tools and analyze their consistency based on the occurrence of certain common contaminant datasets obtained onsite from wells across the study area (Fannakh and Farsang, 2022; Machiwal et al., 2018).

In this study, nitrate (NO_3^-) concentrations were used as the primary contaminant for validation. Given its generally low natural presence in groundwater, elevated levels of nitrate often signify contamination from agricultural fertilizers or wastewater, making it a reliable indicator of anthropogenic influence (Karimzadeh Motlagh et al., 2023). A total of 46 agricultural wells were selected to assess the spatial distribution of nitrate (NO_3^-) concentrations across the study area (Fig. 1). The geographic coordinates of each well were recorded using a Global Positioning System (GPS). Of the total samples, 12 water samples were analyzed in the laboratory of the Department of Geoinformatics, Physical and Environmental Geography, in accordance with Hungarian Standard MSZ EN ISO 13395:1999. The remaining 34 nitrate concentration data were obtained from the Lower Tisza Region Water Directorate (ATIVIZIG), Szeged, through their official groundwater quality monitoring database.

This research assesses groundwater vulnerability using the DRASTIC, GOD, SI, and Fuzzy-enhanced DRASTIC models. To validate the effectiveness of these methodologies, a dual correlation analysis was conducted using Pearson correlation analysis and Spearman's rho correlation, performed with SPSS (Statistical Package for the Social Sciences) version 19.0. This approach is particularly suitable for environmental data, which often exhibit non-normal distributions and may contain outliers, common in studies involving natural variables (Agossou and Yang, 2021).

The application of Pearson's correlation factor (r) is conducted to assess the linear relationships between the observed nitrate concentrations and the model predictions. This method assumes that the data are normally distributed and is sensitive to outliers. This form of analysis is for determining the strength and direction of linear correlations, thereby evaluating the predictive accuracy of each model under linear assumptions (Panagopoulos et al., 2006). Concurrently, Spearman's rho correlation (ρ) is applied to evaluate the monotonic relationships between the same datasets. Unlike Pearson, Spearman's rho correlation factor is not restrained by the general distribution form of two variables and the sample size, it allows for the assessment of relationships where the increases or decreases are consistent but not necessarily linear (Jafari and Nikoo, 2019). This method enhances the validation process by capturing a broader range of potential data interactions, where data distributions can be skewed or interrupted by atypical values.

This dual analytical approach allows for a comprehensive evaluation of each model's accuracy in predicting groundwater vulnerability, highlighting the proportion of variance in nitrate concentrations explained by the vulnerability indices. The integration of these statistical techniques ensures a robust evaluation of the methods' effectiveness, reinforcing their utility in discerning groundwater vulnerability dynamics in Southeast Hungary, offering a reliable foundation for sustainable groundwater management strategies.

3.4.2 Sensitivity Analysis

A comprehensive evaluation of groundwater vulnerability models necessitates a clear understanding of how individual parameters influence assessment outcomes. This study employs single-parameter sensitivity analysis (SPSA) to discern the criticality of parameters within the DRASTIC, Susceptibility Index (SI), and Fuzzy-enhanced DRASTIC methods. While the GOD method assigns equal weighting to its parameters (groundwater occurrence, overlying lithology, and depth to groundwater), the differential impact of individual parameters on the model's output is inherently assumed to be uniform (Foster, 1987).

The sensitivity of each parameter is quantified using a sensitivity index, which measures the change in the vulnerability index relative to the change in the parameter values. This approach quantitatively assesses each parameter's contribution to the model's output, identifying those with significant impacts on the final vulnerability assessment (Singha et al., 2019; Torkashvand et al., 2023). Specifically, the SPSA analysis compares the theoretical weight (assigned by the model) with the effective weight (calculated based on the parameter's actual impact) (Napolitano and Fabbri, 1996). The effective weight (W) of each parameter is computed using the following equation:

$$W = \left(\frac{\mathrm{Pr} \times \mathrm{Pw}}{\mathrm{V}}\right) \times 100 \qquad (4)$$

Where:

- W: effective weight of the parameter,
- Pr: rating value of the parameter,
- Pw: theoretical weight of the parameter, and
- V: overall vulnerability index.

3.4.3 Determining the most suitable method

In the critical evaluation of groundwater vulnerability assessment methodologies, identifying the most effective model is crucial for ensuring reliable and actionable insights. This study determines the most suitable groundwater vulnerability assessment method based on a comprehensive evaluation of predictive accuracy and correlation strength. The methods—DRASTIC, GOD, SI, and Fuzzy-enhanced DRASTIC— are compared by analyzing their vulnerability indices against observed nitrate (NO_3^-) concentrations from 46 wells.

To validate the effectiveness of these methodologies, a dual analytical approach, as discussed in subsection 3.4.1, is utilized, employing both Pearson and Spearman's rho correlations. Performed using SPSS software, these analyses measure the strength and direction of both linear and monotonic relationships between the vulnerability indices and nitrate concentrations. By synthesizing the outcomes of these correlation analyses, the study identifies which approach consistently demonstrates the highest accuracy and strongest correlation with the observed data. The method that exhibits the most robust correlation coefficients across both statistical measures is considered best suited to the hydrogeological conditions of Southeast Hungary. This systematic selection process ensures that the selected method is both statistically validated and practically applicable, thereby providing reliable guidance for groundwater management strategies in the region.

3. 5 Data collection and sources

The compilation of secondary data for this study was collected or derived from a diverse array of sources, including governmental agencies, private sector organizations, and individual scholarly contributions. This broad spectrum of sources ensures a comprehensive dataset that supports the varied hydrogeological analyses conducted in this research. Detailed in Table 9, the data encompasses various types, resolutions, and origins, each contributing uniquely to the study's integrity and depth of analysis.

The thematic layers for delineating the hydrogeological parameters were developed using ArcGIS 10.6.1. This software facilitated the precise integration and spatial analysis of the collected data, enabling the creation of detailed maps that illustrate the geographic distribution and interrelationships of the study's key variables.

__Table 9__. Data and sources utilized in this research. (mbgl: meters below ground level)

Data type	Unit	Resolution	Source	For use with the (name of the method)
Water table depth at 383 locations	mbgl*	Tabular data	Lower Tisza Region Water Directorate of Szeged, Hungary (ATIVIZIG)	○ DRASTIC ○ GOD ○ SI ○ Fuzzy-enhanced DRASTIC
Digital Elevation Model of the study site (for topography parameter): ArcView/ArcInfo Grid files	-	Spatial: 5 m × 5 m	Department of Geoinformatics, Physical and Environmental Geography, University of Szeged, Hungary	○ DRASTIC ○ SI ○ Fuzzy-enhanced DRASTIC
Borehole lithology	-	Tabular data	Lower Tisza Region Water Directorate of Szeged, Hungary (ATIVIZIG)	○ DRASTIC ○ GOD ○ SI ○ Fuzzy-enhanced DRASTIC
Precipitation: point data at meteorological stations; year: 2021	mm	Spatial: 12 stations for precipitation; temporal: monthly	Lower Tisza Region Water Directorate of Szeged, Hungary (ATIVIZIG)	○ DRASTIC ○ SI ○ Fuzzy-enhanced DRASTIC
Land use/cover map; year: 2022	-	Spatial: 15 m × 15 m	ESRI land use\cover model for Landsat 8 imagery	○ SI
Nitrate concentration in shallow aquifer; year: November 2022 - April 2023	mg/l		Personal work and Lower Tisza Region Water Directorate of Szeged, Hungary (ATIVIZIG)	○ DRASTIC ○ GOD ○ SI ○ Fuzzy-enhanced DRASTIC
Soil Map	-	1:100000	(Farsang et al., 2017)	○ DRASTIC ○ GOD ○ Fuzzy-enhanced DRASTIC

Chapter 4: Results and Discussion

This chapter presents the findings from the application of the four groundwater vulnerability assessment approaches—DRASTIC, GOD, SI, and Fuzzy-enhanced DRASTIC—within the context of Southeast Hungary. It details the vulnerability maps produced by each method, highlighting their spatial distinctions and the underlying vulnerability levels identified across the study area. The subsequent section rigorously evaluates the accuracy of each model by performing dual correlation analyses, applying both Pearson and Spearman's rho correlations between the predicted vulnerability indices and observed nitrate concentrations. Additionally, a comprehensive single-parameter sensitivity analysis (SPSA) is conducted to further evaluate the influence of individual parameters on the vulnerability indices, enhancing the precision of the methods used. By synthesizing these findings, the chapter aims to determine the most precise and efficient method for assessing groundwater vulnerability in the context of the region's specific hydrogeological conditions. This structured evaluation contributes to a deeper understanding of regional aquifer susceptibilities. Therefore, enhancing the scientific groundwork for sustainable groundwater protection.

4. 1 Results of DRASTIC groundwater vulnerability mapping

In the assessment of groundwater vulnerability using the original versions of the DRASTIC model, a comprehensive analysis was conducted integrating seven hydrogeological parameters, presented in Figure 6, to produce a vulnerability index map. Each parameter—depth to water table, aquifer recharge rate, aquifer media, soil media, topography, impact of the vadose zone, and hydraulic conductivity—was rigorously rated, and weighted according to established guidelines to reflect its respective impact on groundwater vulnerability. The final vulnerability index (Vi) identifies areas as more sensitive to groundwater contamination compared with others, adopting the classification schema proposed by Corniello et al., (1997) as specified in Table 6. A higher vulnerability index indicates a greater potential for surface contaminants to reach the water table, highlighting areas at risk, whereas a lower index suggests regions where groundwater is comparatively protected from surface contamination.

Figure 11 presents the vulnerability map generated by the DRASTIC method, classifies the study area into zones of low, moderate, and high vulnerability. This classification reveals a significant spatial variation in groundwater susceptibility, with a predominant trend of moderate to high vulnerability, covering 5241 km² (60.32%) and 2909 km² (33.48%) of the total study area, respectively (Table 10).

***Table 10**. Vulnerability assessment criteria used by the three index-overlay methods and their attributes. (GW: Groundwater)*

Vulnerability classes	Attributes	Vulnerability index			
		DRASTIC	GOD	SI	Fuzzy-enhanced DRASTIC
Low	Index range	80 - 120	0.1 - 0.3	< 45	0.25 - 0.4
	Area (% of GW* basin)	6.26	1.26	0.2	2.84
Moderate	Index range	121 - 160	0.3 - 0.5	45 - 64	0.4 - 0.6
	Area (% of GW basin)	60.32	53	22.42	33.18
High	Index range	161 - 200	0.5 - 0.7	65 - 85	0.6 - 0.75
	Area (% of GW basin)	33.48	45.74	77.38	63.91

These areas typically feature shallow water table, presence of sandy sediment composition, low slope, and high recharge rates, all of which contribute to increased vulnerability. Conversely, the low vulnerability regions, constituting about 544 km² or 6.26% of the study area, are primarily located on the eastern side of the Tisza River. These areas are characterized by a higher clay content, which provides a natural barrier against the vertical movement of contaminants due to its lower permeability. This protective characteristic significantly reduces the susceptibility of groundwater to surface contamination in these regions.

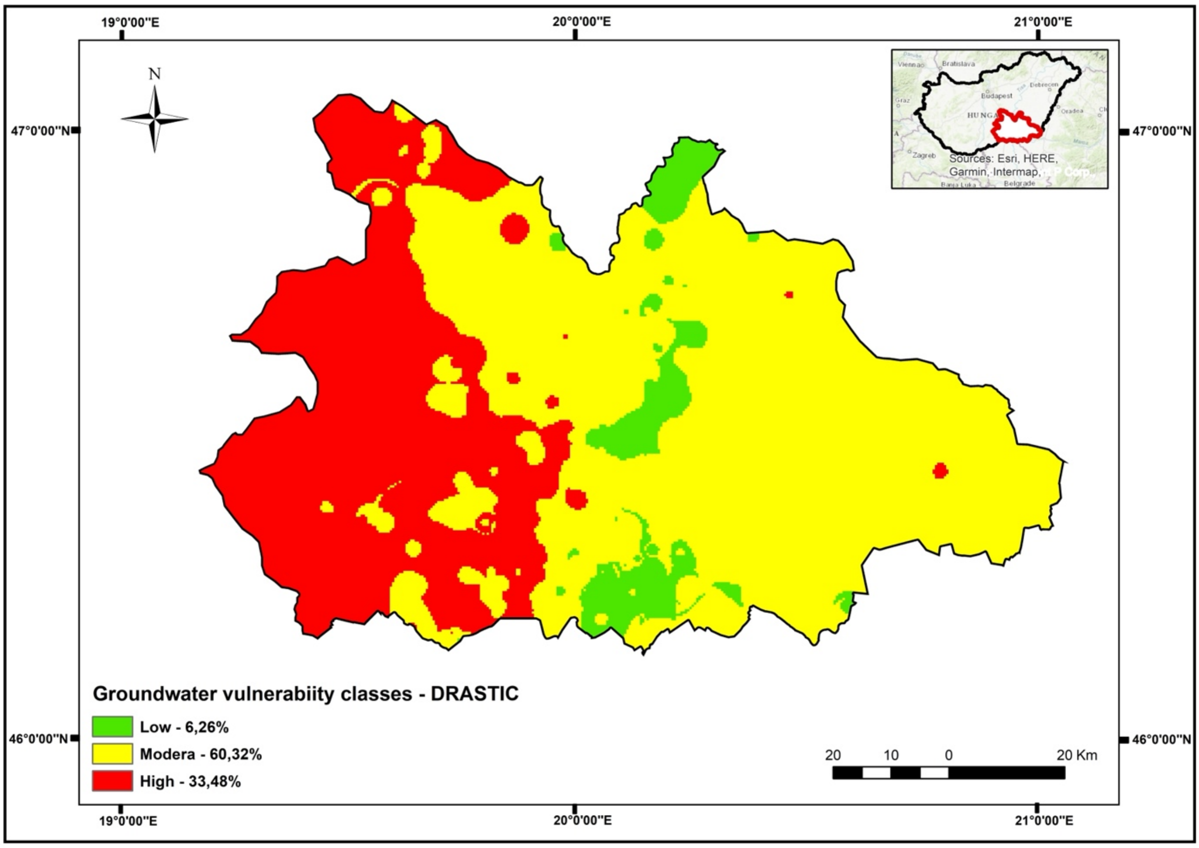


Figure 11. *Spatial distribution of groundwater vulnerability in Southeast Hungary as delineated by the standard DRASTIC method.*

4. 2 Results of GOD vulnerability model

In the assessment of groundwater vulnerability within Southeast Hungary, the GOD model was applied. This method simplifies vulnerability assessment by employing a parametric class system where each of the three parameters—Groundwater occurrence (G), Overlying lithology (O), and Depth to groundwater (D)—contributes equally, with no differential weighting applied, as explained in chapters 2 and 3. Using ArcGIS 10.6.1, the GOD vulnerability index map was computed by multiplying the maps for each parameter, subsequently classifying the final results according to the criteria defined in Table 6.

Figure 12 presents these results, displaying the area segmented into three vulnerability classes—low, moderate, and high. The majority of the area, covering 4606 km² or 53%, is categorized under the moderate vulnerability class, while 2909 km² or 45.74% is classified as high vulnerability (Table 10). This variation according to the GOD model is mainly due to the two layers representing overlying strata and depth to groundwater table, because the groundwater confinement layer does not vary temporarily. Areas classified under the low vulnerability category, covering about 109 km² or approximately 1.26% of the study area, are characterized by high clay content, which offers greater protection against contaminant penetration. This spatial distribution underscores the model's capacity to differentiate regions based on intrinsic geologic and hydrologic conditions, albeit with a broad generalized scope ideal for large-scale assessments of aquifer vulnerability. The same conclusion was drawn by Kazakis and Voudouris, (2011); Ghazavi and Ebrahimi, (2015) and Mfonka, et al, (2018).

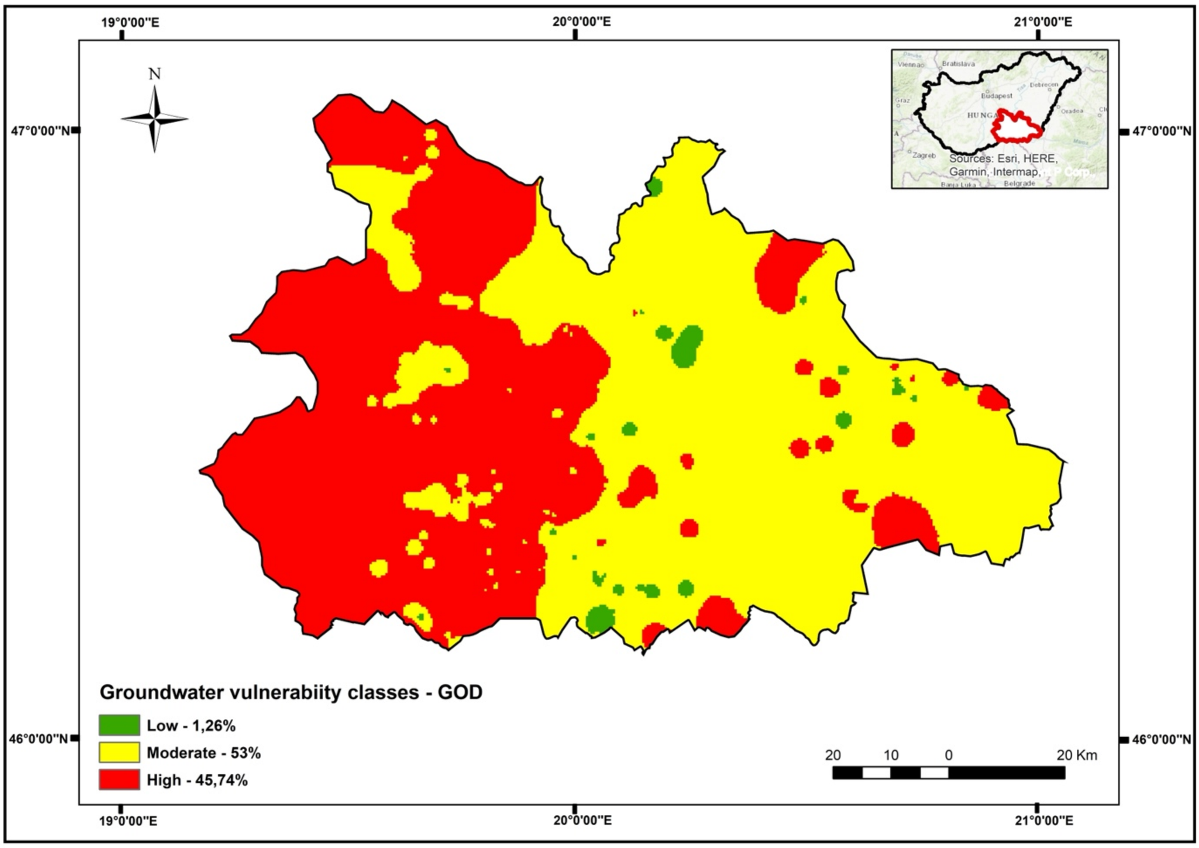


Figure 12. *Intrinsic groundwater vulnerability of Southeast Hungary according to GOD method.*

4. 3 Results of SI groundwater vulnerability mapping

The susceptibility index (SI) method is applied within the Southeast Hungary context to address the significant impacts of agricultural activities. This approach specifically integrates land use factor alongside traditional hydrogeological parameters to address the significant impact of agricultural activities on the aquifer system. This integrative approach enriches the understanding of human activities' influence on groundwater vulnerability (Ghouili et al., 2021). The five layers/parameters of the SI method, presented in Figure 6—depth to groundwater table; aquifer recharge; aquifer media; topographic slope of the land; and land use/cover—were aggregated together applying the weights as depicted in Table 2, to produce a vulnerability index map. Then vulnerability classes for SI method were defined as per the criteria set forth in Table 6.

Figure 13 illustrates the vulnerability map derived from the SI method, the overall picture is clearly distinct from the two vulnerability maps obtained by DRASTIC and GOD models. SI method identifies over 77% of the study area, approximately 6725 km², as highly vulnerable, with the discrepancies between methods occurring primarily in irrigated zones and areas with diverse annual crops. This difference attributed to the fact that SI incorporates land use as a crucial factor, which is not considered by the other two methods. The moderate vulnerability regions, which cover about 1948 km² or 22.42% of the study area, predominantly appear in the western parts, which are characterized by sandy soils, very different from the DRASTIC and GOD vulnerability assessment. These areas are mostly composed of forests and semi-natural zones which are considered non-polluted areas (see Table 5), and the fact that SI method does not consider soil and vadose zone media factors in its assessment. The analysis found a negligible proportion of the area (0.2%) to fall under 'low' vulnerability area. This classification correlates with deeper water tables, lower recharge rates, and the presence of forested and semi-natural areas.

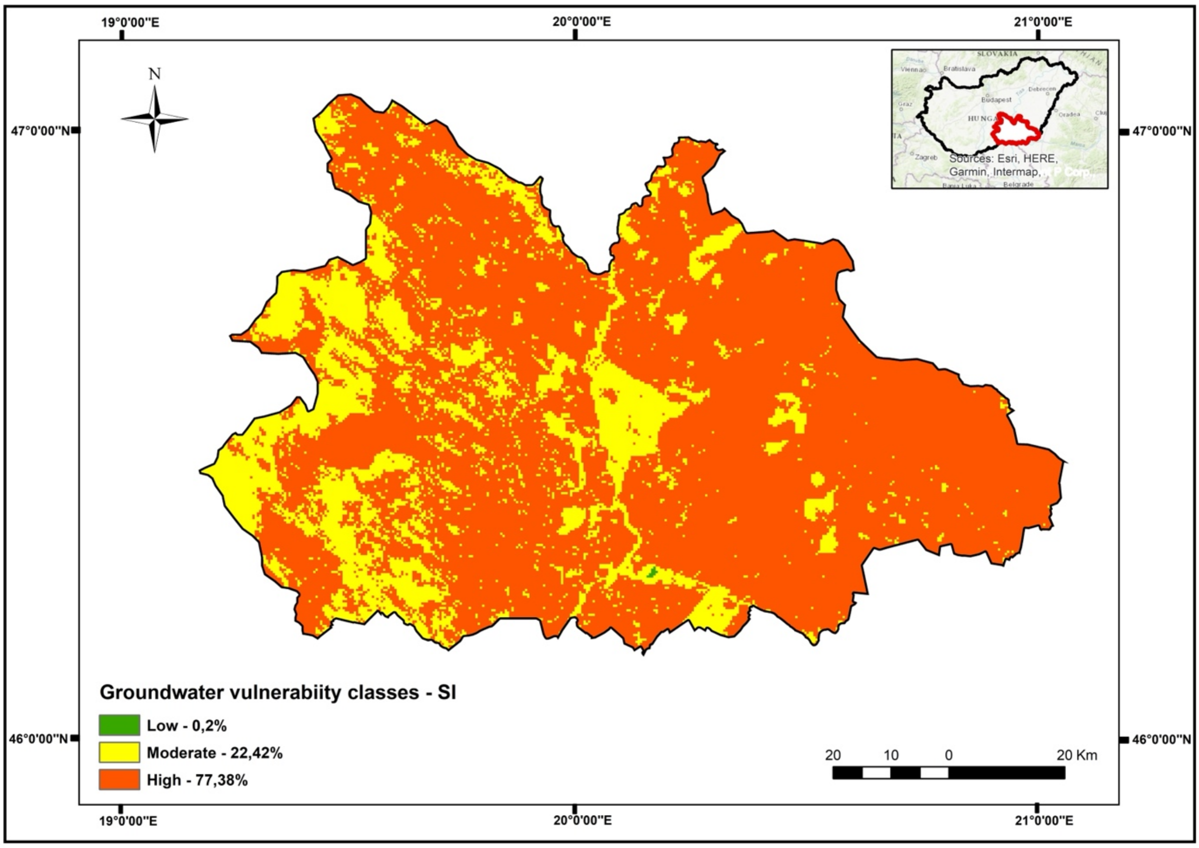


Figure 13. Groundwater vulnerability mapping using the Susceptibility Index (SI) method.

These results are consistent with other studies that have highlighted the importance of integrating land use with intrinsic vulnerability assessments in agricultural regions to improve contamination risk predictions (Anane et al., 2013; Ghouili et al., 2021; Noori et al., 2019; Ribeiro et al., 2017; Stigter et al., 2006).

4. 4 Results of fuzzy-enhanced DRASTIC groundwater vulnerability mapping

The application of the Fuzzy-enhanced DRASTIC model in this study significantly refined the assessment of groundwater vulnerability in Southeast Hungary. This approach addresses the limitations of traditional DRASTIC method, particularly the static nature of parameter ratings and uncertainties in hydrogeological data. The hierarchical fuzzy inference system (FIS) dynamically adjusted the ratings of the seven DRASTIC parameters—depth to water table, aquifer recharge, aquifer media, soil media, topography (slope), vadose zone impact, and hydraulic conductivity—using trapezoidal membership functions to capture the nuanced interactions between these factors. The final output of this system, FIS6, was defuzzified and transformed into a comprehensive vulnerability index, which was subsequently mapped and classified across the study area. This classification delineates the region into three vulnerability categories—low, moderate, and high—through quantile classification, effectively differentiating zones based on their susceptibility to contamination. The model outputs indicate that the fuzzy groundwater vulnerability index (FGWVI) range from 0.25 to 0.75. To better represent natural groupings within the data, the index was reclassified into three categories: low, moderate, and high, using the Jenks natural breaks method (Table 10).

The resulting map, as depicted in Figure 14, shows that approximately 5561 km² or 64% of the study area has high vulnerability, indicating a substantial potential for surface contaminants to penetrate the water table. These high-vulnerability zones are predominantly located in the western part of the study area, characterized by shallow water tables. These zones also feature high recharge rates and consist mainly of sandy sediments, which collectively enhance the risk of contaminant infiltration. Additionally, patches in the southeast part of the study area display high vulnerability due to the presence of sand and sandy loam soils. In contrast, regions along and to the east of the Tisza River were identified as moderately vulnerable, covering about 2883 km² or 33.2% of the area. These zones are characterized by clay loam and silty clay soils, which possess low permeability and substantially reduce infiltration rates. The relatively low recharge rate in these areas diminishes the likelihood of contaminant infiltration, resulting in the moderate vulnerability classification. Only a small fraction (2.8%) of the area exhibits low vulnerability, indicating robust natural barriers. This classification correlates with high clay content and low recharge rates.

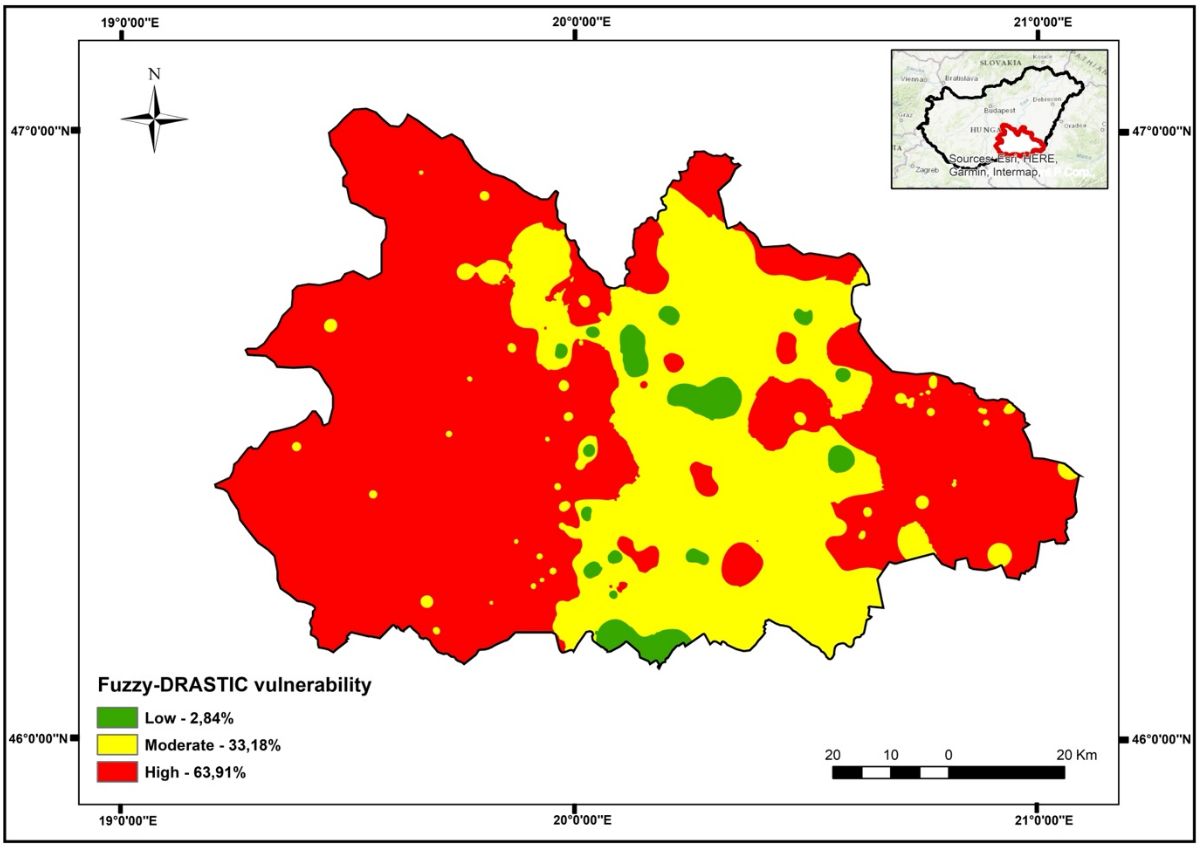


Figure 14. *Interpolated groundwater vulnerability generated through the Fuzzy-enhanced DRASTIC model.*

4. 5 Validation of methodologies using nitrate (NO_3^-) concentrations

Groundwater nitrate (NO_3^-) concentration is commonly used in many studies as a key indicator of anthropogenic impact on aquifers. Given its low natural presence in groundwater, elevated concentrations are typically indicative of contamination from agricultural fertilizers or wastewater, making it a reliable marker of anthropogenic impact and agricultural activities (Halder et al., 2023; Krishna et al., 2015). In this study, NO_3^- concentration was selected as the primary indicator pollutant to validate the predictive accuracy of four groundwater vulnerability models: DRASTIC, GOD, SI, and the Fuzzy-enhanced DRASTIC. Its spatial distribution—NO_3^- concentration—across the study area provides a basis for evaluating which of the applied approaches offers a more precise delineation of vulnerable zones. The analysis incorporated nitrate concentration data from 46 agricultural wells (Fig. 5), collected during the period November 2022 to April 2023, with concentrations ranging from less than 1 mg/l to

25.3 mg/l. According to Hungary's national groundwater quality standards, as established by Regulation 6/2009 (IV.14), the environmental limit for nitrate concentrations in shallow groundwater is 50 mg/L. The measured values in this study, while below this threshold, indicate varying degrees of anthropogenic influence.

To assess the predictive accuracy of the vulnerability models, two correlation coefficients—Pearson's and Spearman's rank correlation—were calculated, examining the relationship between observed nitrate concentrations and the vulnerability indices predicted by each model. The results of these analyses are summarized in Table 11 and the plots illustrated in Fig. 15. Based on Pearson's correlation coefficient, the degree of relationship between GOD and nitrate concentration across the study region exhibited a positive linear correlation, with an r value of 0.592, indicating a moderate linear relationship with nitrate concentrations. The DRASTIC and Fuzzy-enhanced DRASTIC approaches have showed a moderately strong positive linear correlation, with Pearson's r values increasing from 0.601 to 0.69, respectively. This improvement suggests that the Fuzzy-enhanced DRASTIC model provides a more accurate estimation of pollution risk zones compared to the GOD and original DRASTIC models. The SI method demonstrated the highest correlation ($r = 0.751$), indicating a stronger and more significant linear relationship with observed nitrate data. This higher correlation attributed to the inclusion of land use/cover (LU/LC) as a parameter in the SI model, which is a key factor in areas dominated by agricultural activities.

Spearman's rank coefficients, which are less sensitive to non-normal data distributions and outliers, further supported these findings. The correlation between nitrate concentrations and the GOD model was $\rho = 0.583$, while the DRASTIC and Fuzzy-enhanced DRASTIC approaches demonstrated stronger correlations with ρ values of 0.602 and 0.675, respectively. These results align with findings from previous studies (Agossou and Yang, 2021; Ghazavi & Ebrahimi, 2015; Huan et al., 2012). The SI method showed the strongest correlation again outperformed the others ($\rho = 0.812$), demonstrating its robustness in capturing the consistent, yet non-linear relationships between the vulnerability indices and nitrate concentrations. This robust performance can be attributed to the inclusion of the additive parameter LU/LC, which accounts for land use and actual pollution sources, thereby providing a more precise definition of vulnerable areas. These findings are consistent with other studies that have highlighted the importance of integrating land use with intrinsic vulnerability assessments in agricultural regions to improve contamination risk predictions (Anane et al., 2013; Ghouili et al., 2021;

Noori et al., 2019; Ribeiro et al., 2017). Notably, the groundwater vulnerability map generated using the SI approach identified over 77% of the study area as highly vulnerable. A comparison of the SI-based pollution risk map with the land use/cover map revealed that the majority of high-risk zones are concentrated in agricultural and built-up areas, potentially serving as major sources of pollution.

Table 11. *Correlation analysis between groundwater vulnerability indices and nitrate levels*

Vulnerability map	DRASTIC	GOD	SI	Fuzzy-enhanced DRASTIC
Pearson correlation coefficient	0.601*	0.592*	0.751*	0.692*
Spearman rank coefficient	0.602*	0.583*	0.812*	0.675*

* Correlation is significant at the 0.01 level

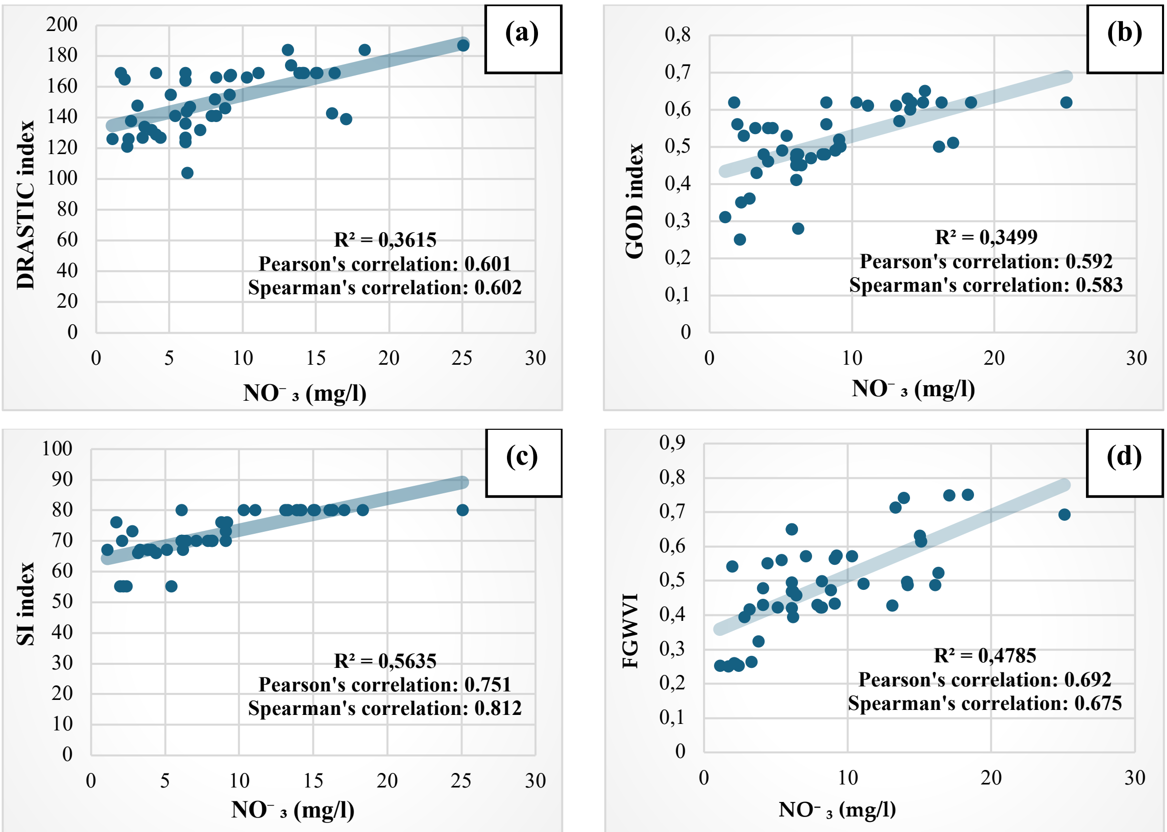


Figure 15. *Linear regression plots between groundwater vulnerability indices and NO_3^- concentration (mg/l)*

4. 6 Single parameter sensitivity analysis

The single parameter sensitivity analysis (SPSA) was conducted to evaluate the relative influence of individual parameters on groundwater vulnerability assessment results for Southeast Hungary, as generated by the DRASTIC, Susceptibility Index (SI), and Fuzzy-enhanced DRASTIC models. This analysis assesses the robustness of the applied methods, examines the sensitivity of the results, and ensures the coherence of the analytical findings, by comparing theoretical parameter weights, which is pre-assigned in the model structure, with their effective weights (Allouche et al., 2017; Kirlas et al., 2022). The effective weight of each parameter was calculated based on its relative contribution to the final vulnerability index. The Table 12 displays the findings of the single parameter sensitivity analysis for the DRASTIC, Fuzzy-enhanced DRASTIC, and SI methods, revealing a variation between each parameter's effective weight and theoretical weight.

For the DRASTIC model, the depth to water table (D) and impact of vadose zone (I) emerged as the most influential parameters, with effective weights of 29.56% and 21.08%, respectively, compared to their theoretical weights of 21.7%. This highlights their dominant role in groundwater vulnerability assessment. These findings align with previous studies (Hamed et al., 2024; Krishna et al., 2015; Panahi et al., 2017; Phok et al., 2021), that also highlight the importance of these parameters in groundwater vulnerability assessments. The high standard deviation (SD = 5.64) for the impact of vadose zone indicates that this parameter vary significantly across locations, emphasizing its spatial sensitivity. This is followed by aquifer recharge parameter, although with a slightly lower effective weight (15.41% instead of 17.4%), though still playing a notable role in defining vulnerability patterns, and this value is consistent with findings from other research (Kirlas et al., 2022; Neshat & Pradhan, 2017). The influence of aquifer media (A) and soil media (S) is relatively similar, with effective weights close to their theoretical values. However, aquifer media exhibited the second highest standard deviation (SD = 4.2%), indicating significant spatial variability. This suggests that lithological differences across the study area strongly impact groundwater vulnerability. Additionally, the Topography (T) parameter demonstrated higher effective weights (7.16%) compared to its theoretical weight (4.3%), with a low standard deviation (SD = 1.12%), reflecting the homogeneous flat terrain of Southeast Hungary. Conversely, hydraulic conductivity (C) showed a considerably lower effective weight (5.91%) compared to its theoretical weight (13%), indicating its limited influence on vulnerability in this context.

Similarly, the Fuzzy-enhanced DRASTIC model, maintained the same dominant parameters with depth to water table (D) (26.71%) and impact of vadose zone (I) (23.42%) exhibiting the highest effective weights. However, unlike the conventional DRASTIC model, where aquifer recharge (R) was the third most influential parameter, the Fuzzy-enhanced approach assigned a higher effective weight to aquifer media (A) (15.21%). This shift reflects the enhanced ability of fuzzy logic to better capture the spatial variability of lithological characteristics on groundwater vulnerability. Aquifer media factor exhibits greater spatial heterogeneity than the recharge rate factor, the fuzzy system prioritizes its varying influence across the study area, leading to a more adaptive and realistic representation of hydrogeological conditions (Fannakh et al., 2025; Khan et al., 2022). Additionally, recharge rate factor interacts early in the hierarchical FIS structure with depth to water table parameter, its influence is partially integrated at an earlier stage, whereas aquifer media enters later, retaining a stronger independent effect (Iqbal et al., 2015; Saranya and Saravanan, 2021). Another key difference from the conventional DRASTIC model is the slight reduction in standard deviations (SD) for most parameters. This reduction in SD suggests that fuzzy logic minimized abrupt transitions in rating assignments, refining the spatial representation of parameter sensitivity, rather than rigid categorical classifications of parameters rating (Gesim & Okazaki, 2018; Nobre et al., 2007; Rezaei et al., 2013). The Topography (T) parameter also demonstrated higher effective weights (6.34%) compared to its theoretical weight (4.3%), reinforcing the homogeneous flat terrain of Southeast Hungary. Conversely, hydraulic conductivity (C) showed a considerably lower effective weight (5.08%) compared to its theoretical weight (13%). This further emphasizes the limited influence of hydraulic conductivity on groundwater vulnerability in this context.

For the Susceptibility Index (SI) model, depth to water table (D), aquifer media (A), and land use/cover (LU/LC) emerged as the most critical parameters, with mean effective weights of 22.15%, 24.19% and 22.87%, respectively, confirming that both hydrogeological and anthropogenic factors contribute significantly to groundwater vulnerability (Anane et al., 2013; Ghouili et al., 2021). Notably, LU/LC exhibited the highest variability (SD = 7.76), indicating that land use practices significantly affect groundwater vulnerability in some areas while having a lesser effect in others. Additionally, topography (T) in the SI model exhibited a slightly higher effective weight (14.02%) than its theoretical weight (12%), reinforcing the findings from DRASTIC and Fuzzy-enhanced DRASTIC, highlighting the importance of the slope in the groundwater vulnerability assessment of the Southeast Hungary.

Overall, the SPSA results highlight the importance of depth to water table (D), impact of vadose zone (I), aquifer recharge (R), and aquifer media (A) as the primary contributors to groundwater vulnerability across all models, with land use/cover (LU/LC) emerging as a critical factor in the SI model. The discrepancies between theoretical and effective weights highlight the limitations of uniform parameter weighting, as seen in the GOD method, and emphasize the value of sensitivity analysis in refining vulnerability models for more accurate predictions.

Table 12. *Statistical summary of single-parameter sensitivity analysis for DRASTIC, SI, and Fuzzy-Enhanced DRASTIC Models*

DRASTIC parameters	Theoretical weight	Theoretical weight (%)	Effective weight (%)			
			Mean	Min	Max	Standard Deviation
Depth to water table (D)	5	21,7	29,56	19,77	42,01	3,36
Aquifer recharge (R)	4	17,4	15,41	8,82	21,47	3,44
Aquifer media (A)	3	13	13,41	8,39	19,2	4,2
Soil media (S)	2	8,7	8,3	4,41	12,08	2,89
Topography (T)	1	4,3	7,16	5,34	9,9	1,04
Impact of vadose zone (I)	5	21,7	21,08	11,81	32,25	5,64
Hydraulic conductivity (C)	3	13	5,91	2,55	15,06	2,42
Fuzzy-enhanced DRASTIC parameters	Theoretical weight	Theoretical weight (%)	Effective weight (%)			
			Mean	Min	Max	Standard Deviation
Depth to water table (D)	5	21,7	26,71	12,66	40,06	3,06
Aquifer recharge (R)	4	17,4	14,58	7,62	19,78	2,68
Aquifer media (A)	3	13	15,21	6,89	21,31	3,73
Soil media (S)	2	8,7	7,92	4,89	13,15	2,38
Topography (T)	1	4,3	6,34	3,63	8,7	1,12
Impact of vadose zone (I)	5	21,7	23,42	12,55	34,41	4,85
Hydraulic conductivity (C)	3	13	5,08	1,86	14,4	2,23
SI parameters	Theoretical weight	Theoretical weight (%)	Effective weight (%)			
			Mean	Min	Max	Standard Deviation
Depth to water table (D)	0,186	18,6	22,15	15,72	31,83	3,17
Aquifer recharge (R)	0,212	21,2	16,75	8,58	27,65	3,21
Aquifer media (A)	0,259	26	24,19	14,81	29,85	4,95
Topography (T)	0,121	12	14,02	11,98	23,95	1,16
Land use/cover (LU/LC)	0,222	22,2	22,87	6,49	32,31	7,76

4. 7 Comparative analysis of methodologies

This study represents one of the first comprehensive efforts to evaluate shallow aquifer vulnerability in Southeast Hungary using four groundwater vulnerability assessment approaches: DRASTIC, GOD, SI, and the Fuzzy-enhanced DRASTIC model. Assessing aquifer vulnerability is a critical step in protecting groundwater resources and guiding land use (LU) planning based on scientific evidence (Halder et al., 2023). Given the hydrogeological complexity and anthropogenic pressures in the region, selecting the most appropriate assessment method remains a challenge, as different models vary in structure, parameter weighting, and sensitivity to local conditions. These challenges are further compounded by the need to balance intrinsic vulnerability factors (e.g., depth to water table, recharge rates, and aquifer media) with external influences such as land use (LU) and contamination sources. To address this, the study applied three widely used GIS-based index-overlay methods—DRASTIC, GOD, and SI—alongside an advanced Fuzzy-enhanced DRASTIC approach, to evaluate their effectiveness at assessing the vulnerability of aquifer in Southeast Hungary to leaching of contaminants from the land surface. Each method integrates key groundwater system attributes, listed in Table 2 and illustrated in Figure 2, which influence the overall vulnerability index (Moraru and Hannigan, 2018; Taghavi et al., 2023). To ensure a robust comparison, this study employs a multifaceted validation approach, integrating both vulnerability map outputs and validation results using nitrate (NO_3^-) concentrations, ensuring that the findings capture both theoretical and field-based perspectives. Additionally, this study incorporated single parameter sensitivity analysis (SPSA) to evaluate the relative influence of each parameter across the methodologies, providing quantitative insights into model performance and parameter impact on vulnerability assessments.

A fundamental distinction between these methodologies lies in how thematic layers are integrated and weighted in groundwater vulnerability assessments. The DRASTIC and SI models use predefined weighting systems, where the relative weights of depth to water table and aquifer recharge are comparable in both methods (22% and 17% in DRASTIC; 19% and 21% in SI). However, aquifer media carries twice the weight in SI (26%) compared to DRASTIC (13%), while hydraulic conductivity is excluded in SI but holds equal weight as aquifer media in DRASTIC. Topography plays a more significant role in SI (12%) than in DRASTIC (4%), while soil media and vadose zone media, which are critical in DRASTIC, are omitted in SI. Instead, SI incorporates land use (LU) with a 22% weight, reflecting its significant influence on contamination risk assessments. Consequently, the SI approach provides a relative evaluation of the groundwater vulnerability, focusing on areas where contaminants are likely to migrate vertically to the aquifer system. In fact, this approach does not identify the flow path that the contaminants will follow within the hydrogeological system. In contrast, while DRASTIC involve in integrates seven intrinsic thematic layers it excludes land use/cover, a factor that significantly influences groundwater susceptibility to pollution. The GOD method employs a parametric class system without weighting, treating all parameters equally. This simplifies its structure but fails to account for the varying influence of different hydrogeological factors, potentially overestimating or underestimating vulnerability in specific conditions. The Fuzzy-enhanced DRASTIC model retains the original DRASTIC weighting factors to preserve the model's original structure and ensure comparability with previous studies, while introducing fuzzy logic adjustments to handle the inherent variability and uncertainty in parameter ratings, and refine parameter interactions, allowing for greater adaptability in parameter influence based on local hydrogeological conditions. This hybrid approach combines the strengths of the DRASTIC framework with the flexibility of fuzzy logic, providing a more refined vulnerability index without altering the fundamental principles of the original method.

The comparative analysis of the applied methodologies is grounded on both nitrate (NO_3^-) validation results and findings from single parameter sensitivity analysis (SPSA), which quantify the influence of individual parameters on vulnerability assessments. All four methods classified the study area into low-, moderate-, and high-vulnerability zones, with a predominant trend of moderate to high vulnerability. In many areas, this tendency seems to be driven by shallow water table, presence of sandy sediments, a high recharge rate and the predominance of high agricultural activity areas in land use. The areas of high vulnerability highlighted by Shrestha et al., (2017) and Kouz et al., (2020) on the basis of the application of the DRASTIC, GOD and SI methods in comparable geomorphic settings (i.e. shallow aquifers with a lithological nature consisting of sand and silt, and high recharge rate) increase their susceptibility to contamination. However, the extent and distribution of high-vulnerability areas varied significantly between models, driven by differences in parameter influence observed in the SPSA results.

The DRASTIC model assigned the highest vulnerability to areas with a shallow water table, permeable vadose zone, and high recharge rates, consistent with its high effective weights for depth to water table (29.56%), impact of vadose zone (21.08%), and aquifer recharge (15.41%). The Fuzzy-enhanced DRASTIC model demonstrated improved spatial accuracy of vulnerability zones, reducing abrupt classification transitions by applying adaptive rating adjustments through fuzzy logic. One of the key strengths of the hierarchical FIS is its ability to handle the imprecision inherent in environmental data. Traditional DRASTIC method assigns fixed ratings to parameters, which may not reflect real-world variations. By contrast, the fuzzy-enhanced DRASTIC model applies fuzzy membership functions to each parameter, allowing for gradual transitions between vulnerability classes, this flexibility has improved the model's accuracy, particularly in distinguishing between moderate and high vulnerability zones. Notably, aquifer media factor (15.21%) became the third most influential parameter in Fuzzy-enhanced DRASTIC, replacing recharge (R), which dominated the conventional DRASTIC model. This shift suggests that fuzzy logic captures lithological variability more effectively, reducing the dominance of fixed recharge rates. In contrast, the GOD method identifies a greater extent of highly vulnerable zones compared to the DRASTIC approach. This discrepancy is likely attributable to the GOD method's more generalized framework and its underlying assumption that groundwater vulnerability is only influenced by three parameters. This difference aligns with findings reported by Kazakis and Voudouris, (2011) in their study of the alluvial aquifer in the Florina Basin, Greece, where the GOD model produced a broader high-vulnerability classification compared to DRASTIC method. The SI model is clearly distinct from the three vulnerability maps. SI approach identifies over 77% of the study area, as highly vulnerable, primarily occurring in irrigated zones and areas with diverse annual crops. This difference attributed to the fact that SI incorporates land use patterns, which is absent in the other methods. Furthermore, the DRASTIC and GOD methods focus exclusively on assessing intrinsic vulnerability and do not incorporate pollution risk. As defined by Foster, (1987), pollution risk arises from the interplay between aquifer vulnerability and the magnitude of pollutant loading, a factor not addressed by these approaches. The SPSA results confirm that depth to water table (D), aquifer media (A), and land use/cover (LU/LC) emerged as the most influential parameters in SI, with mean effective weights of 22.15%, 24.19% and 22.87%, respectively.

Validation of the vulnerability maps was conducted by correlating vulnerability indices with nitrate (NO_3^-) concentrations from 46 monitoring wells. Both Pearson's and Spearman's correlation coefficients were computed to quantify the relationships between vulnerability indices and nitrate measurements. The GOD method exhibited the weakest correlations

(Pearson's r = 0.592; Spearman's ρ = 0.583), reflecting its limitations in capturing detailed vulnerability nuances needed in complex hydrogeological settings. The DRASTIC method demonstrated moderate predictive accuracy, with Pearson's and Spearman's correlation coefficients of 0.601 and 0.602, respectively, while its Fuzzy-enhanced counterpart demonstrated slightly improved accuracy (Pearson's r = 0.69; Spearman's ρ = 0.675). However, the exclusion of LU in both DRASTIC approaches limited their effectiveness in agriculturally dominated regions. In contrast, the SI method outperformed the other approaches, achieving the strongest correlations with nitrate concentrations (Pearson's r = 0.751; Spearman's ρ = 0.812). This superior performance is attributed to the inclusion of LU as a parameter, which directly accounts for the impact of agricultural activities on contamination risk, confirming its ability to capture complex interactions between hydrogeological factors and agricultural land use underscores its effectiveness in regions where nitrate contamination is primarily driven by agricultural activities. The SPSA results explain these validation outcomes, as the SI model's high effective weights for aquifer media and land use allowed it to better capture nitrate contamination trends. In contrast, the DRASTIC models' and GOD approach exclusion of land use limited their ability to predict contamination in agricultural regions.

These findings highlight the importance of integrating anthropogenic factors, such as land use, and advanced techniques, such as fuzzy logic, into groundwater vulnerability assessments. The results suggest that the SI method is particularly well-suited for regions with intensive agricultural activities, such as Southeast Hungary. While the Fuzzy-enhanced DRASTIC model offers a valuable alternative for areas with complex hydrogeological settings. Overall, the comparative analysis highlights the need for tailored vulnerability assessments that account for both intrinsic hydrogeological factors and anthropogenic influences, providing policymakers with reliable tools for protecting groundwater resources in agriculturally dominated regions.

To enhance the clarity and readability of the comparative analysis, a summary table was prepared to synthesize the key aspects of the four applied methods: DRASTIC, GOD, SI, and the Fuzzy-enhanced DRASTIC. The table integrates validation outcomes (correlation coefficients with nitrate concentrations), identifies the most influential parameters based on SPSA, and outlines each method's major strengths and limitations, together with their relative data and computational requirements. This consolidated overview provides a concise comparative framework, facilitating a clearer understanding of the trade-offs between methodological simplicity, predictive accuracy, and practical applicability in the context of Southeast Hungary.

Table 13. *Comparative summary of the applied groundwater vulnerability assessment methods (DRASTIC, GOD, SI, and Fuzzy-enhanced DRASTIC) in Southeast Hungary.*

Method	Validation (Pearson r / Spearman ρ)	Most Influential Parameters (SPSA)	Strengths	Limitations	Computational Requirements
DRASTIC	r = 0.601 ρ = 0.602	* Depth to water (29.6 %); * Vadose zone (21.1 %); * Recharge (15.4 %)	Widely applied; integrates multiple intrinsic factors; strong comparability across studies.	Fixed ratings limit adaptability; excludes land use.	Moderate – requires 7 hydrogeological layers, GIS overlay
GOD	r = 0.592 ρ = 0.583	Not applicable (equal weighting of 3 factors)	Simple, fast application; suitable for preliminary assessments.	Over-generalized; fails to account for the varying influence of different hydrogeological factors; poor in agricultural settings	Low – requires 3 parameters, easy mapping
SI	r = 0.751 ρ = 0.812	* Aquifer media (24.2 %); * Land use (22.9 %); * Depth to water (22.2 %)	Strongest predictive accuracy; incorporates land use; robust in agricultural areas.	Higher computational demand; requires fuzzy expertise; still excludes land use	Moderate – 5 parameters (hydrogeological + land use)
Fuzzy-enhanced DRASTIC	r = 0.690 ρ = 0.675	* Depth to water table (26.7 %); * Vadose zone (23.4 %) * Aquifer media (15.2 %)	Captures uncertainties; smooth transitions; improved spatial accuracy; adaptive to heterogeneity.	Higher computational demand; requires fuzzy expertise; still excludes land use	High – 7 parameters + fuzzy inference system (MATLAB, GIS)

Chapter 5: Conclusions and Recommendations

Chapter 5 synthesizes the key findings, implications, and recommendations derived from the comparative evaluation of four groundwater vulnerability assessment methodologies—DRASTIC, GOD, SI, and Fuzzy-enhanced DRASTIC—applied to the environmental and hydrogeological conditions of Southeast Hungary. The chapter begins by summarizing the key findings, including the results of the vulnerability assessments, the comparative analysis of the methods, and the insights from the single parameter sensitivity analysis (SPSA). Emphasis is placed on the superior performance of the SI method in regions with intensive agricultural activities and the improved accuracy of the Fuzzy-enhanced DRASTIC model in capturing spatial variability and refining vulnerability classifications. It then explores the theoretical and practical implications of these findings for effective groundwater management. Recommendations for future research are presented, focusing on methodological refinements, data integration, and the development of hybrid models. The chapter also acknowledges the limitations of the study, and proposes strategies to overcome these challenges in future work. Finally, policy recommendations are provided to guide sustainable groundwater management in Southeast Hungary, with an emphasis on stakeholder engagement and the implementation of vulnerability-based land use regulations.

5. 1 Key Findings

The detailed systematic study conducted in this research evaluated the effectiveness of four groundwater vulnerability assessment methodologies—DRASTIC, GOD, SI, and the Fuzzy-enhanced DRASTIC—applied within the specific hydrogeological and land-use context of Southeast Hungary. The objective was to determine the most suitable approach for assessing groundwater vulnerability in a region characterized by intensive agricultural activities and heterogeneous hydrogeological conditions. Nitrate (NO_3^-) concentrations in groundwater were used as the primary metric for validating each method's effectiveness. Additionally, a single-parameter sensitivity analysis (SPSA) was conducted to assess the influence of individual parameters on the vulnerability indices, providing deeper insights into the robustness and reliability of each method. The results provide valuable insights into the performance, limitations, and applicability of these methods within the regions. The key findings of the study are summarized as follows:

- The generated vulnerability maps indicate that approximately 95% of the region is at moderate to high risk of contamination. This trend is primarily driven by factors such as low slope, shallow water table, presence of sandy sediments, a high recharge rate and the predominance of intensive agricultural practices in land use. These factors collectively enhance the susceptibility of groundwater to contamination from surface pollutants.
- The DRASTIC method, a widely used index-overlay approach, identified 33% of the study area as highly vulnerable, demonstrating a moderate positive correlation with nitrate concentrations (Pearson's $r = 0.601$; Spearman's $\rho = 0.602$). While its comprehensive integration of seven hydrogeological parameters makes it a robust tool for intrinsic vulnerability assessment, its reliance on static ratings and exclusion of land use (LU) data reduces its accuracy in highly agricultural regions, where anthropogenic influences significantly impact contamination risks.
- The Fuzzy-enhanced DRASTIC model demonstrated improved predictive accuracy, classifying 64% of the study area as highly vulnerable and yielding a stronger correlation with nitrate concentrations (Pearson's $r = 0.69$; Spearman's $\rho = 0.675$). By incorporating fuzzy logic to refine parameter ratings and minimize abrupt classification transitions, this model enhanced sensitivity to hydrogeological variability while preserving the structured framework of DRASTIC. Notably, the shift in parameter

influence observed in the SPSA results, particularly the increased role of aquifer media, highlights fuzzy logic's ability to better capture lithological variability.

- The GOD method identified 45% of the study area as highly vulnerable but exhibited the weakest correlation with nitrate concentrations (Pearson's $r = 0.592$; Spearman's $\rho = 0.583$). This is primarily due to its simplistic, unweighted classification framework, which considers only groundwater confinement, overlying lithology, and depth to water table. The absence of hydrogeological complexity and land use considerations reduces its capacity to accurately reflect real-world contamination dynamics.
- In contrast, the SI method outperformed all other approaches, classifying 77% of the study area as highly vulnerable and achieving the strongest correlation with nitrate concentrations (Pearson's $r = 0.751$; Spearman's $\rho = 0.812$). This superior performance is attributed to the incorporation of land use patterns alongside hydrogeological factors, which significantly enhanced its ability to predict contamination risks associated with agricultural pollutants. The SPSA results further confirm the dominant influence of land use (22.87%), aquifer media (24.19%), and depth to water table (22.15%) in the SI model, underscoring the importance of incorporating anthropogenic variables in vulnerability assessments.
- These findings emphasize the importance of integrating anthropogenic factors (e.g., land use) and advanced modeling techniques (e.g., fuzzy logic) into groundwater vulnerability assessments to improve predictive accuracy. The study highlights that traditional models, such as DRASTIC and GOD, may not fully capture contamination risks in agricultural landscapes, whereas SI and Fuzzy-enhanced DRASTIC offer more context-sensitive vulnerability assessments.
- The generated vulnerability maps of Southeast Hungary represent a valuable decision-support tool for policymakers and water resource managers to achieve sustainable land-use planning, groundwater protection zoning, and the development of targeted monitoring programs. These maps can guide the balanced use of territory and reduce anthropogenic pressure in areas naturally prone to groundwater contamination, thereby supporting long-term groundwater protection and resource sustainability within the region.

5. 2 Theoretical and practical implications

This research represents one of the first comprehensive evaluations of shallow aquifer vulnerability in Southeast Hungary, through the application of four groundwater vulnerability assessment approaches—DRASTIC, GOD, SI, and the Fuzzy-enhanced DRASTIC model. The study makes significant theoretical contributions to the field of groundwater vulnerability assessment by demonstrating the necessity of integrating anthropogenic factors (e.g., land use) and advanced modeling techniques (e.g., fuzzy logic) to improve predictive accuracy. The findings reinforce that the SI method, which incorporates land use alongside traditional hydrogeological parameters, outperforms other methods in predicting contamination risk in agricultural regions, achieving the strongest correlation with nitrate concentrations (Pearson's $r = 0.751$; Spearman's $\rho = 0.812$). This superior performance demonstrates the importance of considering human-induced pressures on groundwater systems, as land use plays a pivotal role in controlling contaminant transport and aquifer recharge patterns.

Similarly, the Fuzzy-enhanced DRASTIC model effectively addresses the limitations of static parameter ratings inherent in traditional DRASTIC approach, providing a more adaptive and spatially accurate representation of groundwater vulnerability. The model's ability to gradually transition parameter influences rather than relying on fixed rating classes has led to a notable increase in high-vulnerability zones identified compared to the conventional DRASTIC method. This enhancement is reflected in its improved correlation with nitrate concentrations (Pearson's $r = 0.69$; Spearman's $\rho = 0.675$). The integration of hierarchical fuzzy inference systems (FIS) refined parameter interactions, particularly reducing rating subjectivity and improving sensitivity to lithological variability. These methodological advancements highlight the value of incorporating flexible, data-adaptive frameworks within intrinsic vulnerability assessments, enhancing their ability to capture nuanced variations in groundwater susceptibility even in the absence of explicit contamination source data.

On a practical level, the findings offer valuable tools for effective groundwater management in Southeast Hungary. The vulnerability maps generated by the study serve as a scientific basis for understanding shallow aquifer vulnerability in the region for identifying and prioritizing areas at high risk of contamination, enabling local authorities to implement targeted monitoring programs and the implementation of measures to mitigate the impact of agricultural practices. The results emphasize the necessity of spatially explicit management approaches that align land use planning with groundwater vulnerability zones. This is particularly relevant for agricultural land use regulations, where vulnerability maps can support sustainable irrigation practices and pollutant control measures. Furthermore, this study emphasizes the importance of stakeholder engagement, demonstrating how scientific outputs, such as vulnerability maps, can serve as effective communication tools for raising awareness about groundwater contamination risks and promote collaborative efforts to protect water resources. By integrating these findings into water resource management policies, regulatory frameworks can incorporate adaptive measures that balance economic development with groundwater protection goals. Overall, this research not only advances scientific understanding of groundwater vulnerability assessment methodologies but also provides actionable insights for evidence-based groundwater protection strategies, ensuring long-term sustainability of water resources in Southeast Hungary and comparable regions worldwide.

5. 3 Limitations of the study

Despite the robust methodological framework and comprehensive evaluation conducted in this study, certain limitations must be acknowledged. These limitations relate primarily to data availability and resolution, methodological constraints, the generalizability of results, fuzzy logic subjectivity, and policy implementation challenges.

Given the relatively large size of the study area (~8700 km^2), the unavailability of densely distributed values for the various thematic layers was the main barrier to generating a high-resolution vulnerability maps. Coarser spatial datasets can lead to generalization errors, particularly in heterogeneous hydrogeological environments. While GIS-based interpolation techniques were used to address spatial gaps, the accuracy of vulnerability maps is inherently dependent on the resolution of input data. Furthermore, the spatial resolution of validation data must be acknowledged. Although nitrate (NO_3^-) measurements from 46 monitoring wells provided a reasonable basis for model validation, this sampling density may not fully capture the spatial variability in contamination levels, particularly in a heterogeneous aquifer system.

The study applied index-overlay models (DRASTIC, GOD, and SI), which rely on predefined weighting schemes. While these models are widely used for groundwater vulnerability assessment, they are subject to inherent subjectivity in parameter weighting and ratings. The DRASTIC and SI models assign fixed weights to hydrogeological parameters, which may not fully account for spatial variations in parameter influence. Additionally, the GOD model does not employ parameter weighting, potentially leading to oversimplification in certain areas where hydrogeological factors exert varying levels of control over groundwater vulnerability.

The Fuzzy-enhanced DRASTIC model was introduced to address the limitations of static parameter ratings. However, the design of fuzzy membership functions remains a subjective process, as it depends on expert judgment and predefined rules, which can introduce potential biases. Additionally, the computational complexity of hierarchical fuzzy inference systems (FIS) present practical challenges for real-time applications and require significant computational resources compared to simpler index-based models. Future research could explore machine learning-driven fuzzy logic optimizations to enhance automation and reduce subjective dependencies.

While the methodologies applied in this study are widely used in groundwater vulnerability assessment, the findings are specific to Southeast Hungary and may require modifications when applied to other regions. The hydrogeological conditions, land use practices, and pollution sources in the study area are unique, influencing the relative importance of individual parameters in vulnerability assessments. For instance, the dominance of agricultural activities in Southeast Hungary increased the predictive strength of the SI method, but this may not hold true in other regions where contamination sources differ. Additionally, while the integration of fuzzy logic demonstrated improvements in spatial accuracy, its applicability should be validated in diverse hydrogeological settings. Future studies should test the adaptability of this method across different environmental conditions to enhance their generalizability.

Although this study provides scientific insights into groundwater vulnerability, the translation of findings into policy and management decisions presents challenges. The successful implementation of vulnerability-based groundwater protection strategies requires collaboration between researchers, policymakers, and local stakeholders. However, integrating scientific assessments into regulatory frameworks is often hindered by institutional barriers, lack of enforcement mechanisms, and competing land-use priorities.

5. 4 Recommendations for future research

Building upon the findings and limitations identified in this study, several areas for future research can be explored to enhance the accuracy, applicability, and policy relevance of groundwater vulnerability assessments.

- Future studies should explore the integration of high-resolution remote sensing data for land use, soil properties, and recharge rate estimation to reduce spatial generalization errors and improve model precision in heterogeneous hydrogeological settings. Additionally, expanding the spatial and temporal resolution of validation datasets—particularly for groundwater nitrate (NO_3^-) concentrations—would enhance model validation robustness by capturing seasonal and long-term contamination trends. The use of multi-year groundwater quality data would further allow for trend analysis, improving the predictive capability of vulnerability models over time.

- Future research should focus on refining vulnerability models by integrating machine learning (ML) techniques, such as artificial neural networks (ANNs), support vector machines (SVMs), or random forest (RF) algorithms. These approaches would allow for data-driven parameter weighting optimizations, reducing the reliance on predefined expert-based assignments.
- Conducting longitudinal studies on groundwater vulnerability would help capture temporal variations in aquifer susceptibility and assess how climate change and evolving land-use patterns impact groundwater contamination risks. Future research should explore hydro-climatic modeling approaches to analyze the effects of shifting precipitation patterns, extreme weather events, and prolonged droughts on groundwater recharge and contamination susceptibility.
- While the Fuzzy-enhanced DRASTIC model demonstrated improved predictive accuracy, its applicability should be tested across different hydrogeological and climatic conditions. Conducting comparative assessments in regions with varying lithologies, and pollution sources would refine the adaptability of the methodology and improve its predictive robustness in different environmental contexts.
- While this study focused on intrinsic vulnerability assessments, future research should incorporate numerical groundwater flow and contaminant transport simulations to enhance risk prediction accuracy. Models such as MODFLOW and MT3DMS could provide critical insights into pollutant dispersion pathways, travel times, and groundwater flow dynamics, allowing for more precise assessments of contamination risks. This would enable decision-makers to not only identify areas prone to contamination but also understand how pollutants migrate through the aquifer system over time, leading to more effective groundwater protection strategies.

5. 5 Policy recommendations

The findings of this study underscore the urgent need for science-based policy interventions to safeguard groundwater resources in Southeast Hungary. Given the region's high vulnerability to contamination, particularly from agricultural activities, the following policy recommendations are proposed to enhance groundwater management, strengthen regulatory enforcement, and promote stakeholder engagement:

- Policymakers should integrate vulnerability-based land use planning into environmental policies, ensuring that high-risk areas identified in vulnerability maps are designated as protected zones. In such areas, restrictions on intensive agricultural activities, industrial waste disposal, and urban expansion should be enforced to minimize contamination risks. Additionally, establishing mandatory groundwater monitoring programs with higher spatial and temporal resolution is essential for tracking nitrate concentrations and other pollutants over time. The implementation of real-time monitoring systems, coupled with open-access groundwater databases, would enhance transparency and data-driven decision-making among researchers, policymakers, and environmental agencies.
- Given the strong correlation between land use practices and groundwater vulnerability, sustainable agricultural policies should be prioritized. Government should encourage precision agriculture techniques, such as controlled fertilizer application, optimized irrigation strategies, and crop rotation, to reduce excessive nitrogen leaching into aquifer. Furthermore, raising awareness among agricultural stakeholders through educational campaigns and training programs will further promote sustainable land and water management practices.
- Environmental Impact Assessments (EIAs) should be mandatory for all new development projects in areas identified as high-vulnerability zones, ensuring that groundwater contamination risks are systematically evaluated before project approval. Furthermore, regulatory agencies should periodically review and update environmental guidelines to reflect emerging groundwater risks associated with urbanization, industrialization, and climate change.
- Effective groundwater management also requires multi-stakeholder collaboration and community engagement. The Lower Tisza Water Management Directorate (ATIVIZIG) should establish a regional groundwater governance structure by bringing together scientists, policymakers, local authorities, and community representatives to develop integrated water management strategies. Additionally, public participation in groundwater monitoring programs, including citizen science initiatives and community-led water quality assessments, would foster greater accountability and collective responsibility for groundwater protection.
- Finally, continued research and technological advancements should be encouraged to support innovative groundwater protection strategies. Investment in smart groundwater

monitoring systems, artificial recharge methods, and AI-driven contamination prediction models would enhance long-term resilience in groundwater management. Moreover, fostering cross-disciplinary collaborations between hydrologists, geospatial analysts, and policymakers will ensure that scientific findings are effectively translated into policy frameworks. By implementing these policy recommendations, decision-makers can proactively mitigate contamination risks, ensure long-term groundwater sustainability, and support the region's broader environmental and economic goals.

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Abstract

Groundwater represents a critical resource in Southeast Hungary, serving as a critical supply for drinking water, industry, and especially agriculture. This region's flat, fertile landscape supports intensive farming – Over 65% of the area is devoted to intensive crop cultivation, including maize, sunflower, and wheat – leading to heavy use of fertilisers and pesticides. These agricultural practices, coupled with the region's susceptibility to severe and prolonged droughts, pose significant risks to both groundwater quantity and quality. Consequently, the aquifer of Southeast Hungary face persistent threats of contamination and over-exploitation. While prior studies in Southeast Hungary have addressed groundwater quality and quantity concerns, a comprehensive vulnerability assessment comparing multiple methodological approaches was lacking. This research addresses this knowledge gap by conducting a comprehensive evaluation of groundwater vulnerability – the susceptibility of groundwater to contamination from surface activities – in Southeast Hungary through a comparative analysis of multiple assessment approaches—DRASTIC, GOD, the Susceptibility Index (SI), and a Fuzzy-enhanced DRASTIC model. The overarching aim of the research is to determine the most effective model for mapping and understanding groundwater vulnerability in Southeast Hungary and to generate scientifically tools that support sustainable water management, land use planning, and policy development.

The study begins with an in-depth review of established methodologies for assessing groundwater vulnerability, with a focus on their theoretical underpinnings, spatial modeling techniques, and limitations when applied to real-world conditions. These insights informed the selection of three standard index-overlay models—DRASTIC, GOD, and SI—as well as the development of a fuzzy logic-based enhancement of the DRASTIC model. The standard DRASTIC method integrates seven intrinsic hydrogeological factors—Depth to water table, Recharge rate, Aquifer media, Soil media, Topography, Impact of the vadose zone, and Hydraulic conductivity—each assigned a fixed weight based on expert judgement. The DRASTIC Index is computed by combining these weighted ratings, producing a spatially explicit vulnerability map. The GOD model simplifies vulnerability assessment by focusing on only three parameters: Groundwater occurrence (confined/unconfined), Overlying lithology, and Depth to water table. It assumes equal weighting of these parameters, offering ease of application at the expense of adaptability. In contrast, the SI method introduces land use/land cover as a key parameter, thereby extending the traditional concept of intrinsic vulnerability toward a more risk-based approach. The SI method uses five parameters—Depth, Recharge,

Aquifer media, Topography, and Land use/cover—weighted and aggregated to reflect both hydrogeological and anthropogenic drivers of vulnerability. To address limitations associated with fixed parameter ratings, a Fuzzy-enhanced DRASTIC model was developed using a Hierarchical Fuzzy Inference System (FIS). While retaining the original DRASTIC parameters and weights to ensure methodological comparability, the fuzzy system replaced discrete parameter ratings with continuous fuzzy membership functions, thereby allowing for more continuous transitions in the vulnerability index. Each of the four methods was applied across the same study area using thematic GIS layers, including interpolated surfaces for each parameter. The resulting maps were validated using nitrate (NO_3^-) concentrations from 46 groundwater wells, sampled between November 2022 and April 2023. Pearson's and Spearman's correlation coefficients were used to quantify the relationship between model outputs and observed nitrate levels. Additionally, a Single-Parameter Sensitivity Analysis (SPSA) was also conducted for the DRASTIC, SI, and fuzzy-DRASTIC models to determine the relative influence of each parameter based on its effective weight in the final vulnerability index.

The results demonstrated significant spatial variability in vulnerability across Southeast Hungary, with a predominant trend of moderate to high vulnerability. In many areas, this tendency seems to be driven by shallow water table, presence of sandy sediments, a high recharge rate and the predominance of high agricultural activity areas in land use. However, the extent and distribution of high-vulnerability areas varied significantly between models, driven by differences in parameter influence observed in the SPSA results. The conventional DRASTIC model classified approximately 33% of the region as highly vulnerable and achieved moderately strong correlation with nitrate data (Pearson's $r = 0.601$; Spearman's $\rho = 0.602$), confirming its utility as a baseline method while also revealing its limitations in predictive precision. The simpler GOD method identified ~45% as high vulnerability but yielded the weakest correlation with observed contamination (Pearson's $r = 0.592$; Spearman's $\rho = 0.583$), reflecting its limited parameter scope. In contrast, methodologies integrating anthropogenic factors and advanced modeling achieved higher predictive accuracy. The SI method, which incorporates land-use alongside intrinsic parameters, outperformed all others by delineating about 77% of the area as highly vulnerable and attaining the strongest correlation with groundwater nitrate levels (Pearson's $r = 0.751$; Spearman's $\rho = 0.812$). Similarly, the fuzzy-enhanced DRASTIC model classified ~64% of the area as highly vulnerable and improved the predictive correlation (Pearson's $r = 0.690$; Spearman's $\rho = 0.675$), due to its refined parameter ratings that better capture hydrogeological variability. These findings underscore the advantages of integrating land-use data and fuzzy logic adjustments into groundwater vulnerability assessments to improve predictive accuracy, as the traditional models, such DRASTIC and GOD, may not fully capture contamination risks in intensive agricultural landscapes and complex hydrogeological settings.

The SPSA findings further provided insights into parameter influence across models. In the conventional DRASTIC method, the most influential parameters were depth to water table (29.56% effective weight) and impact of the vadose zone (21.08%), while aquifer recharge emerged as the third most important. In contrast, the fuzzy-enhanced DRASTIC model maintained depth and vadose zone as dominant parameters (26.71% and 23.42%, respectively) but elevated the importance of aquifer media (15.21%) above recharge rate, highlighting the fuzzy system's enhanced capacity to capture lithological heterogeneity. Standard deviations across parameters were slightly reduced in the fuzzy model, indicating a more balanced representation of parameter influence. For the SI model, aquifer media, depth to water, table and land use/cover were the most critical parameters (each contributing roughly 22–24% to the vulnerability index). These findings reinforce the argument that land use must be considered alongside intrinsic hydrogeological properties in regions facing agricultural pressures. While the GOD model inherently employs a parametric class system without weighting, treating all parameters equally. This simplifies its structure but fails to account for the varying influence of different hydrogeological factors, potentially overestimating or underestimating vulnerability in specific conditions. Across all approaches, parameters related to vadose zone media, aquifer media, and water table depth emerged as critical factors, and the inclusion of anthropogenic variable (land use) in the SI method significantly improved its predictive capability, the superior performance of the SI method suggests it as the effective tool for assessing groundwater vulnerability within Southeast Hungary, while the fuzzy logic approach offers a promising enhancement for index-based models in capturing gradational changes in vulnerability.

Through its comparative analysis and introduction of a fuzzy logic enhancement, this PhD research contributes to the broader understanding of groundwater vulnerability assessment both in theory and practice. It demonstrates the importance of tailoring vulnerability assessments to regional conditions, integrating both intrinsic and anthropogenic factors, and employing adaptive models capable of representing spatial complexity. For Southeast Hungary, the research outcomes have important practical implications for sustainable water resource management within the region. The resulting vulnerability maps serve as valuable decision-support tools for land-use planning, groundwater protection zoning, and the design of targeted monitoring programs. By identifying zones of high contamination risk, local authorities and stakeholders can prioritize interventions and balance land-use practices to protect vulnerable areas. The thesis recommends incorporating these vulnerability assessment findings into policy and planning, including stakeholder engagement and the implementation of vulnerability-based land-use regulations, to guide long-term groundwater protection in Southeast Hungary. Lastly, the study highlighted and shed light on some areas that need future studies. These include (1) the integration of high-resolution remote sensing data to improve the spatial representation of land use, soil properties, and recharge estimations, thereby reducing generalisation errors in heterogeneous hydrogeological settings. Expanding both the spatial and temporal resolution of nitrate concentration data would also enhance validation robustness and support long-term trend analysis, (2) future research should focus on integrating machine learning techniques—such as artificial neural networks, support vector machines, or random forest algorithms. These approaches would allow for data-driven parameter weighting optimizations, reducing the reliance on predefined expert-based assignments, (3), longitudinal investigations studies to capture temporal dynamics in groundwater vulnerability under shifting land use and climatic conditions, (4) incorporating numerical simulations of groundwater flow and contaminant transport, such as MODFLOW and MT3DMS, would enable more accurate modelling of pollutant pathways and travel times, thereby supporting more targeted and effective groundwater protection strategies.

Publications related to the scientific topic of the dissertation

Hungarian Scientific Bibliography (MTMT) identifier: 10081888

1) **Fannakh, A.,** Farsang, A. DRASTIC, GOD, and SI approaches for assessing groundwater vulnerability to pollution: a review. Environ Sci Eur 34, 77 (2022). https://doi.org/10.1186/s12302-022-00646-8

   IF_{2024} = 6.0

2) **Fannakh, A.,** Károly, B., Farsang, A. et et Ben Ali, M., Evaluation of index-overlay methods for assessing shallow groundwater vulnerability in southeast Hungary. Appl Water Sci 15, 118 (2025). https://doi.org/10.1007/s13201-025-02463-9

   IF_{2024} = 5.7

3) **Fannakh, A.,** Károly, B., Fannakh, M., & Farsang, A. (2025). Assessment and Validation of Shallow Groundwater Vulnerability to Contamination Based on Fuzzy Logic and DRASTIC Method for Sustainable Groundwater Management in Southeast Hungary. Water, 17(5), 739, 23 p. (2025). https://doi.org/10.3390/w17050739

   IF_{2024} = 3.0

Statement of the Supervisor

I, Dr. Károly Barta, hereby declare, in my capacity as supervisor, that the dissertation authored by Fannakh Abdelouahed (Neptun code: T2DSI4), entitled *"Assessment of Groundwater Vulnerability for Sustainable Water Resource Management in Southeast Hungary: A Comparative Analysis of Methodological Approaches"*, is the candidate's own original work, prepared under my supervision.

I confirm that the candidate made substantial and independent contributions to the research results presented and discussed in the dissertation. Furthermore, I certify that the thesis fully meets the formal, academic, and professional standards set by the Doctoral School of Environmental Sciences of the University of Szeged, and by the Faculty of Science and Informatics, Department of Physical and Environmental Geography.

Accordingly, I support the submission of this dissertation for public defense.

Date: 09/09/2025

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