

Review

A Review of Multi-Criteria Decision Analysis (MCDA) for Cultural Heritage Risk Assessment Using Geospatial and Earth Observation Data

Kyriakos Michaelides *  and Athos Agapiou 

Department of Civil Engineering and Geomatics, Faculty of Engineering and Technology, Cyprus University of Technology, Saripolou 2-8, 3036 Limassol, Cyprus

* Correspondence: km.michaelides@edu.cut.ac.cy

Abstract

Cultural heritage sites are affected by environmental and anthropogenic pressures that require decision-analysis methods capable of combining heterogeneous datasets while accounting for uncertainty. Multi-Criteria Decision Analysis (MCDA), particularly when integrated with Geographic Information Systems (GIS) and Earth Observation (EO) data, is widely used in geospatial analysis involving multiple, often conflicting criteria. This review examines the evolution, application domains, and methodological challenges of MCDA in cultural heritage risk assessment. The literature indicates a predominant reliance on weighting-based methods, especially the Analytic Hierarchy Process (AHP) combined with GIS-based weighted overlay techniques, while uncertainty treatment, temporal monitoring, validation, and multi-threat applications remain limited. Three illustrative applications show that asset-level, regional susceptibility, and historic-urban frameworks address complementary decision needs but differ in their data, expertise, and institutional requirements. Recent developments show a trend to combine MCDA with fuzzy logic, machine learning, and uncertainty modeling, although methodological consistency across these approaches remains uneven. The findings suggest that multi-criteria risk assessment for cultural heritage may depend less on introducing new analytical techniques and more on improving the integration of existing methods. Incorporating repeatable environmental observations, sensitivity analyses, multi-threat assessment, and stakeholder participation may support a more coherent and reproducible approach to heritage-risk assessment.

Keywords: Multi-Criteria Decision Analysis; cultural heritage; risk assessment; Earth Observation; GIS; spatial decision support; spatial MCDA; uncertainty analysis; multi-threat assessment



Academic Editor: Antonio Vettore

Received: 23 June 2026

Revised: 4 August 2026

Accepted: 11 August 2026

Published: 13 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Cultural heritage sites face various environmental and human pressures that can threaten their physical state and historical value. Factors such as climate change, environmental degradation, urban growth, tourism, and socio-economic changes rarely occur in isolation; instead, their combined effects often produce cumulative impacts that heighten vulnerability across heritage landscapes [1–3]. Therefore, heritage vulnerability cannot be fully understood through single-hazard assessments or static analysis methods alone. More comprehensive evaluation techniques are necessary to capture the complex, spatially variable, and multidimensional nature of risk conditions.

UNESCO [4] underscores the importance of proactive disaster risk management in cultural heritage contexts, encouraging a transition from reactive responses to prevention, preparedness, and long-term resilience. Within this perspective, risk assessment is a key process for identifying hazards, analyzing vulnerabilities, and prioritizing mitigation actions before damage becomes irreversible. Risk assessment, therefore, functions not only as a technical procedure but also as a planning mechanism supporting conservation priorities, resource allocation, and policy development under changing environmental conditions [1,5].

Assessing heritage risk remains inherently challenging because physical characteristics, environmental processes, management capacity, and cultural values must be considered simultaneously. Available evidence is often heterogeneous: Earth Observation (EO) datasets and ready products, Geographic Information Systems (GIS) layers, field observations, historical records, and qualitative information may all contribute to assessments, although these sources differ considerably in scale, completeness, and resolution [6,7]. Such conditions require analytical approaches that are able to integrate diverse forms of information while explicitly addressing assumptions and uncertainty.

Multi-Criteria Decision Analysis (MCDA) provides a structured means of evaluating several factors that influence heritage risk, including exposure to hazards, physical vulnerability, environmental conditions, cultural significance, and management capacity [8]. The use of GIS enables their geographical combination, while EO provides repeatable observations of environmental conditions and landscape change [9]. Their integration can therefore produce maps or rankings that help heritage professionals compare sites, identify priority areas, and evaluate potential interventions [10]. These outputs are intended to support, not replace, professional and community judgment [11].

Indeed, MCDA has gained considerable attention as a decision-support approach for problems involving multiple and potentially conflicting criteria. While Cinelli et al. [12] emphasize the value of MCDA for structuring complex decision problems, Malczewski and Rinner [13] place stronger emphasis on its spatial implementation within GIS-based environments. This distinction is relevant to cultural heritage assessment, where both methodological transparency and spatial representation are required.

The integration of MCDA with GIS and EO has extended its application across several related domains [14,15]. Environmental management and sustainability applications use MCDA for resource allocation, conservation planning, and environmental evaluation [16–18], while ecosystem-management studies apply it to prioritize interventions under limited resources and competing stakeholder interests [19,20]. Natural hazards and spatial risk assessment form another major application area, where MCDA is combined with GIS and EO-derived indicators to produce susceptibility and risk maps [14,21,22]. Disaster-risk research increasingly uses repeated EO observations across prevention, preparedness, response, and recovery activities [23]. Spatial-planning and land-use applications use MCDA to compare planning scenarios and development alternatives [24,25], while engineering and structural-health monitoring integrate repeated sensor and geospatial observations to support condition assessment and maintenance decisions [26]. Across these domains, recurring requirements include the transparent integration of heterogeneous criteria, incorporation of stakeholder preferences, explicit consideration of uncertainty, and compatibility with geospatial data infrastructures [14,15].

Despite these developments related to the implementation of MCDA, existing studies continue to rely heavily on relatively simple workflows, such as the Analytic Hierarchy Process (AHP) combined with GIS-based weighted overlay techniques. Similar trends were reported by Mardani et al. [27], while Appiotti et al. [28] demonstrated their applicability in cultural heritage risk-assessment contexts. Although these methods remain widely adopted

due to their simplicity and compatibility with raster-based datasets, they may oversimplify interactions among criteria, allow compensatory effects between risk factors, and provide only a limited representation of uncertainty. Likewise, the incorporation of EO-derived indicators and temporal datasets varies substantially across the literature [29,30].

This review critically examines the evolution of a range of MCDA approaches, their principal application domains, and methodological limitations for cultural heritage risk assessment based on geodata. Specifically, the objectives are to: (i) analyze the development of MCDA methods and their integration with GIS and EO technologies; (ii) evaluate their application across environmental management, hazard assessment, and cultural heritage; and (iii) identify research gaps and future directions for improving spatial decision-support systems for heritage risk assessment.

To guide this analysis, the study is structured around the following research questions:

- (1) How have MCDA approaches evolved in response to increasing data complexity and spatial decision-making requirements?
- (2) What are the dominant MCDA methods and application domains relevant to cultural heritage risk assessment?
- (3) What methodological limitations and research gaps exist in current MCDA applications?
- (4) How can integrated approaches combining spatial data, uncertainty modeling, and decision-analysis techniques improve cultural heritage risk assessment under multi-threat conditions?

Although previous reviews have examined MCDA applications in environmental management and decision-support systems, few have focused specifically on cultural heritage, and even fewer have addressed uncertainty representation, multi-threat assessment, and the operational integration of EO-derived indicators into heritage-risk workflows. This review compares developments across MCDA, GIS, EO, environmental assessment, and cultural heritage to identify transferable practices and persistent gaps. It is intended for researchers and practitioners working across disciplines, including geomatics, Earth Observation, hazard and risk assessment, heritage conservation, and spatial planning.

2. MCDA for Cultural Heritage Threat Assessment

Cultural heritage sites are subject to a wide range of environmental and anthropogenic pressures that can affect their physical condition, historical significance, and long-term preservation. These pressures often interact across spatial and temporal scales, creating multi-threat conditions that are difficult to evaluate using isolated analytical procedures. For clarity, a hazard or threat is a potentially damaging natural or human-induced process. Exposure describes the presence of heritage assets in areas that may be affected, whereas vulnerability is their susceptibility to damage. Risk arises from the interaction of these components and, in heritage contexts, is also shaped by the asset's significance and the capacity of institutions and communities to prepare for, respond to, and recover from damaging events [1,4,28]. Therefore, heritage risk assessment often requires integrating heterogeneous datasets, expert knowledge, and geospatial indicators into a single evaluation process.

Figure 1 presents a generalized workflow integrating EO data, GIS analyses, MCDA methods, and uncertainty evaluation within cultural heritage risk assessment.

In this context, MCDA offers a structured approach to heritage-related decision problems involving multiple, potentially conflicting criteria. Rather than evaluating each risk factor separately, MCDA enables the organization of factors, the assignment or derivation of their relative importance, the combination of their values, and the comparison of alternative sites, areas, or management interventions.

Nevertheless, methodological inconsistencies remain evident across published studies, particularly in method selection, criterion weighting, uncertainty treatment, and spatial implementation [12,14,15]. The uneven incorporation of EO-derived indicators [29,30], together with differences in spatial resolution, classification thresholds, and validation procedures, can substantially influence results and hinder comparisons between studies.

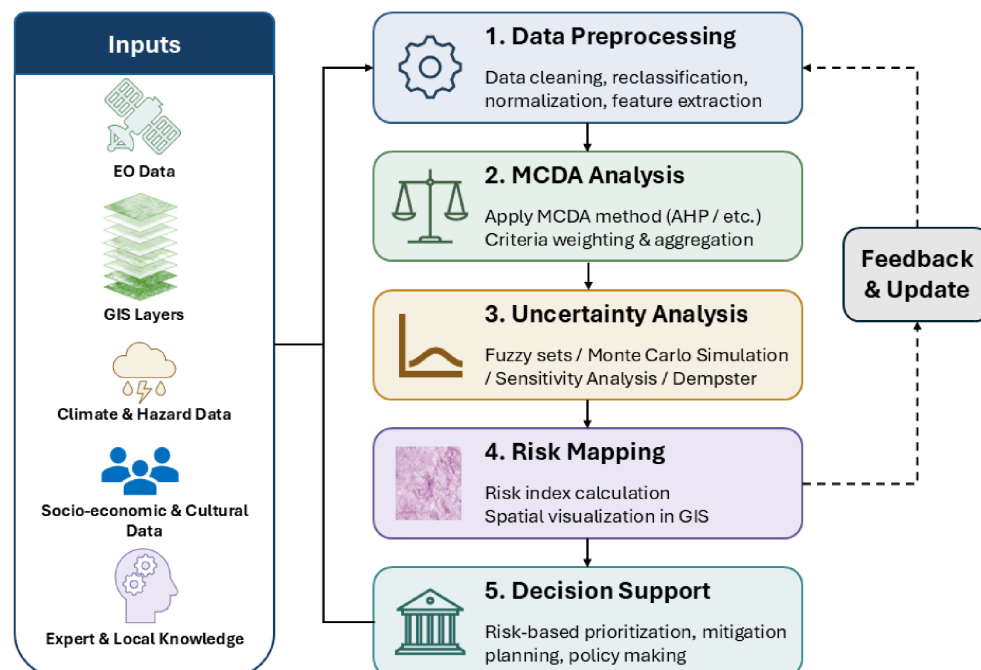


Figure 1. Integrated workflow for cultural heritage risk assessment combining EO data, GIS, MCDA methods, uncertainty analysis, and decision-support processes.

2.1. Threat Categories Addressed in Heritage Studies

Cultural heritage risk assessment generally considers two broad categories of pressures: natural hazards and anthropogenic influences. Natural hazards include earthquakes, flooding, landslides, coastal erosion, wildfires, and climate-related processes that can affect structural integrity [31]. Anthropogenic pressures include urban expansion, infrastructure development, tourism, pollution, and land-use change, all of which may alter environmental conditions surrounding heritage assets [32]. The distinction between these categories is not always absolute. For example, inappropriate land-use planning, vegetation removal, or inadequate drainage may increase the impacts of flooding, erosion, or landslides, while climate change can alter the frequency or intensity of several existing hazards [1,4].

In practice, these pressures rarely occur independently. Interactions among hazards may produce cumulative or compounding effects; urban growth, for example, may increase exposure to flooding, while climate variability may intensify existing environmental stressors. A heritage property may therefore face multiple simultaneous or sequential pressures, such as intense rainfall causing erosion and slope instability, followed by structural deterioration and reduced site accessibility. Nevertheless, a substantial proportion of published studies continues to evaluate hazards individually rather than under multi-threat conditions.

MCDA methods permit multiple categories of threats to be examined within common assessment procedures by combining environmental indicators, socio-economic variables, and cultural characteristics [33,34]. However, different threats cannot always be combined directly because their spatial extent, measurement units, temporal behav-

ior, and consequences may differ substantially. Accordingly, criteria typically require standardization, weighting, and transparent aggregation before they can be compared or combined.

Heritage risk assessment must also account for the characteristics and context under study. Archaeological sites, historic buildings, monuments, cultural landscapes, and historic urban areas may differ in materials, spatial extent, condition, use, cultural values, and management requirements. Consequently, a method appropriate for prioritizing spatially distributed archaeological sites may not be directly applicable to the structural assessment of an individual historic building. This contextual variability is important when interpreting and comparing the applications reviewed in the following sections.

2.2. MCDA Methods Applied in Heritage Contexts

Existing heritage-risk methodologies have progressed from indicator-based models that combine structural, environmental, and institutional variables for site prioritization [1,35] to broader frameworks that incorporate hazard, exposure, vulnerability, and adaptive capacity [36,37]. Nevertheless, many applications remain hazard-specific despite increasing recognition of interacting hazards and threats [38]. Static interpretations of vulnerability also persist, even as environmental and socio-economic conditions change over time [39,40].

A wide range of MCDA techniques has been applied within cultural heritage assessment, although weighting-based methods continue to dominate published studies. AHP combined with GIS-based weighted overlay procedures remains among the most frequently used combinations for integrating spatial indicators with expert judgment. Mardani et al. [27] identify weighting-based approaches among the most widely adopted multiple-criteria decision-making techniques, while Agapiou et al. [41], Michaelides and Agapiou [42], and Nicu [43] illustrate how GIS, EO data, and AHP-based workflows can be incorporated within cultural heritage risk and susceptibility assessment.

The predominance of AHP should not be interpreted solely as evidence of methodological superiority. Rather, it reflects its accessible hierarchical structure, interpretability, and compatibility with raster-based GIS workflows. However, results may be sensitive to criterion selection, expert judgments, pairwise comparisons, and compensatory aggregation, particularly when criteria interact or uncertainty is substantial.

Alternative decision-analysis techniques have also been applied in heritage contexts. Ferretti et al. [44], for example, used Multi-Attribute Value Theory to evaluate the reuse of historic buildings. Outranking and compromise-based approaches can support the assessment of trade-offs, compromise solutions, or non-compensatory relationships. Fuzzy MCDA has been adopted to represent ambiguity within expert judgment, while machine-learning methods may generate susceptibility indicators that are subsequently incorporated into MCDA procedures [45,46]. However, these methods require suitable data, technical expertise, interpretability, and validation.

Spatial variability strongly influences heritage vulnerability, and GIS-based MCDA enables the incorporation of environmental and socio-economic indicators into geographically explicit assessments [14,34]. Satellite observations additionally provide repeatable information on environmental conditions and landscape dynamics, facilitating monitoring across local and regional scales [47,48]. Duțu et al. [49] further highlighted the potential of open-access EO datasets for monitoring environmental threats affecting remote archaeological sites and supporting proactive heritage management strategies, including applications at Delos Island. However, EO-derived indicators are frequently represented as static layers rather than used to assess change over time. Experience from disaster-risk and engineering applications shows that repeated observations can support change detection and the updating of assessments as conditions evolve [23,26].

2.3. Cultural Heritage Applications

The practical implications of these methodological choices become clearer when applications operating at different spatial and decision scales are compared. At the asset level, Appiotti et al. [28] developed a multicriteria model that integrates hazard, vulnerability, and heritage-related indicators for immovable cultural assets exposed to fire, earthquakes, and floods. The model supports comparisons among assets and potential interventions but depends on detailed information, expert-completed assessments, and stakeholder-derived weights. At the regional scale, Nicu [43] compared AHP, frequency ratio, and statistical index methods for landslide susceptibility mapping in an area with endangered cultural heritage. AHP achieved the highest reported predictive performance among the three methods, underscoring the value of model comparison and validation. However, the resulting assessment remained hazard-specific and did not incorporate heritage significance, structural condition, or interactions with other threats.

At the historic-urban scale, Ravankhah et al. [1] assessed natural hazards and climate-change influences in the Historic Centre of Rethymno, Greece. Their framework combined climate information, GIS-based spatial analysis, and a hazard-analysis matrix to examine sudden- and slow-onset processes and communicate their spatial distribution to stakeholders. This broader perspective supports the assessment of changing hazard conditions but requires heterogeneous datasets, climate projections, specialist knowledge, and institutional coordination. Collectively, these examples show that asset-level multicriteria models, regional susceptibility assessments, and historic-urban multi-hazard frameworks address different but complementary decision needs.

The choice of an MCDA method should therefore depend on the decision problem, heritage context, spatial scale, available evidence, treatment of uncertainty, required stakeholder participation, and intended management decision. No single method is appropriate for every cultural heritage application.

3. Methodology

This review examines the development and application of MCDA within spatial decision-support systems, with particular emphasis on cultural heritage risk assessment using GIS and EO data. The study was designed as a narrative review with thematic synthesis. It aims to compare methodological approaches, their principal advantages and limitations, their application across different decision contexts, and the research gaps that affect their use in cultural heritage risk assessment.

Relevant publications were identified through searches in Scopus, Web of Science, and Google Scholar using combinations of terms including “MCDA”, “GIS-based decision analysis”, “Earth Observation”, “cultural heritage”, “risk assessment”, and “spatial decision support”. The searches were conducted during manuscript preparation and last updated in July 2026. Additional search terms included “multi-criteria decision analysis”, “remote sensing”, “vulnerability”, and “hazard assessment”. Because terminology varies across MCDA, geomatics, environmental risk, and cultural heritage research, the database searches were supplemented with backward and forward citation tracking of relevant methodological reviews and applied studies.

The review focused on peer-reviewed journal articles and review papers addressing methodological developments, spatial applications, and cultural heritage assessment. Selected institutional publications were also considered if they contributed to the interpretation of cultural heritage risk and management requirements. Publications were deemed relevant if they addressed MCDA methodology, GIS or EO integration, environmental and hazard assessment, spatial decision support, or cultural heritage vulnerability and risk

management. Titles and abstracts were assessed for relevance, and full texts were consulted as needed. Duplicate publications identified across searches were retained only once.

The identified literature was organized and synthesized thematically, focusing on methodological classification, application domains, and recurring limitations. Attention was given to spatial data integration, uncertainty treatment, stakeholder participation, operational implementation, and the emergence of hybrid or data-driven approaches. Heritage-related examples, drawn predominantly from European and Mediterranean contexts, included archaeological sites, historic buildings, urban heritage, and cultural landscapes. To broaden the methodological comparison, the review also considered international evidence from environmental management, engineering, spatial planning, and disaster-risk assessment. Representative studies were compared in terms of their methodological strengths, limitations, data requirements, and suitability for different cultural heritage decision contexts.

4. Classification of MCDA Methods by Spatial Suitability

Multi-Criteria Decision Analysis includes a diverse set of methods for evaluating problems involving multiple, often conflicting criteria. When combined with GIS and EO data, these methods can operate within spatial environments to generate suitability, vulnerability, and risk assessments [13,50].

However, MCDA techniques differ considerably in terms of spatial applicability, uncertainty treatment, computational complexity, and compatibility with EO-derived indicators. Distinguishing these methodological characteristics is therefore necessary when selecting approaches for geospatial analyses and cultural heritage assessment. Spatial applicability can be evaluated by whether a method can be implemented with continuous raster data, is better suited for ranking discrete spatial alternatives, or supports a particular stage of the analytical workflow. Table 1 summarises the principal MCDA families according to their spatial suitability and their typical role within EO/GIS workflows.

Table 1. Classification of MCDA methods for spatial decision support.

MCDA Family	Representative Methods	Typical Role in EO/GIS	Potential Role in CH Assessment
Weight-based	AHP, ANP, SAW/WLC, OWA	Raster-based suitability and risk mapping	Risk, vulnerability, and priority mapping
Distance & Compromise-based	TOPSIS, VIKOR, SCP	Spatial ranking and compromise solutions	Comparison and prioritization of sites or interventions
Outranking	ELECTRE, PROMETHEE	Ranking discrete spatial alternatives	Evaluation of heritage sites, management strategies, or conservation interventions
Utility-based	MAUT, SMART	Preference modeling (non-spatial)	Evaluation of conservation and management alternatives
Uncertainty-aware	Fuzzy MCDA, DST	Handling vagueness and evidence conflict	Assessment involving uncertain indicators, thresholds, or expert judgments
Data-driven and ML methods	RF, SVM, CNN	Spatial susceptibility modeling and pattern detection	Production of susceptibility or damage-related layers for integration into MCDA
Complementary methods	Delphi, Entropy, PCA, DEMATEL, Monte Carlo	Criteria weighting support, dimensionality reduction, uncertainty, and sensitivity analysis	Expert elicitation, criteria refinement, sensitivity analysis, and robustness assessment

4.1. Weight-Based Spatial MCDA

Weight-based techniques represent the most widely used category of MCDA within GIS-based spatial analyses. These methods combine multiple criteria by assigning relative importance values and aggregating them into composite indices. In geospatial applications, approaches such as the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Simple Additive Weighting (SAW), Weighted Linear Combination (WLC), and Ordered Weighted Averaging (OWA) are frequently adopted because of their compatibility with raster environments [13,27,50].

In EO workflows, indicators such as topography, land cover, climatic conditions, and proximity variables are commonly standardized before aggregation to produce continuous suitability or risk surfaces. Their widespread use in environmental assessment, hazard mapping, and cultural heritage studies largely reflects computational efficiency and ease of implementation within GIS platforms [14,15,41].

Saaty [51] introduced AHP as a hierarchical procedure for decomposing decision problems and deriving criterion weights through pairwise comparisons. Owing to its relative simplicity and interpretability, AHP remains one of the most frequently applied techniques. ANP extends this logic by incorporating interdependencies among criteria, although greater methodological complexity often limits broader application [52]. SAW and WLC rely on linear combinations of weighted criteria, whereas OWA introduces varying levels of compensation by reflecting different decision-maker preferences through ordered weights [13,53].

Despite their extensive application, several limitations persist. Most weighting-based methods assume compensatory behavior, meaning that weak performance on one criterion may be offset by stronger performance on another. In hazard and heritage-risk assessment, such compensation may conceal critical vulnerabilities. Weight derivation also frequently relies on expert judgment, while uncertainty in datasets and model structure often receives limited attention.

These limitations have prompted the integration of weighting methods with fuzzy logic, sensitivity analysis, and hybrid workflows that incorporate EO indicators and machine-learning outputs. Although weighting-based techniques remain practical options for EO-supported heritage assessment, methodological choices regarding weighting procedures, aggregation methods, and uncertainty treatment continue to influence analytical outcomes substantially. Table 2 summarises the main characteristics, advantages, and limitations of commonly used weighting-based methods.

Table 2. Weight-based spatial MCDA methods.

Method	Primary Role	Main Advantage	Main Limitation	Typical Use in EO/GIS Workflow
AHP	Criteria structuring and weighting	Transparent; intuitive; widely used	Subjective weights; limited uncertainty handling	Early stage: define the criteria hierarchy and derive weights
ANP	Weighting with interdependencies	Captures interactions among criteria	High complexity; strong expert dependence	Early stage: modeling interrelated criteria
SAW/WLC	Linear spatial aggregation	Simple; efficient; fully GIS-compatible	Full compensation; ignores uncertainty	Middle stage: generate composite suitability/ risk maps
OWA	Controlled aggregation	Models risk attitude and partial compensation	Subjective order weights	Middle stage: scenario-based aggregation

4.2. Distance and Compromise-Based MCDA Methods

Distance and compromise-based techniques rank alternatives according to their proximity to ideal conditions within a multidimensional decision space. Rather than relying exclusively on additive aggregation, these approaches aim to identify solutions that best balance competing criteria by minimizing the distance from ideal and anti-ideal reference points. In geospatial applications, methods such as TOPSIS, VIKOR, and Spatial Compromise Programming (SCP) have been adapted for use with GIS and EO-derived datasets [13,54,55].

Within EO-supported applications, these methods are typically implemented after criterion standardization, enabling spatial units, such as pixels or zones, to be ranked by performance across multiple indicators. One advantage is their ability to account for trade-offs among conflicting criteria while producing ranking outputs applicable to environmental assessment and hazard evaluation [21,27].

Hwang and Yoon [56] introduced TOPSIS as a ranking method based on proximity to ideal and anti-ideal solutions. Opricovic and Tzeng [57] later developed VIKOR as a compromise-ranking technique that balances collective utility against individual regret, making it applicable when strong conflicts exist among criteria. SCP extends compromise-programming principles within raster environments by identifying locations closest to predefined ideal conditions [13].

Despite these characteristics, several constraints emerge when such methods are applied to large EO-supported analyses. Outcomes may be sensitive to data standardization procedures, distance metrics, and parameter selection, all of which can substantially affect comparability and the stability of results. Furthermore, uncertainty representation and the interdependencies among criteria are rarely explicitly addressed. Implementation in continuous raster environments may therefore be less straightforward than with weighting-based methods [54,55].

Distance and compromise-based methods remain useful for trade-off analysis and comparative spatial ranking (Table 3). Their application in the cultural heritage literature examined is less frequently represented than weighting-based approaches, particularly in contexts requiring continuous susceptibility mapping.

Table 3. Distance and Compromise-based MCDA methods.

Method	Primary Role	Main Advantage	Main Limitation	Typical Use in EO/GIS Workflow
TOPSIS	Ranking based on the ideal solution	Intuitive; easy to interpret; widely used	Sensitive to normalization; limited uncertainty handling	Middle stage: spatial ranking and benchmarking
VIKOR	Compromise ranking	Balances group utility and individual regret	Parameter sensitivity; less GIS-native	Middle stage: trade-off and compromise analysis
SCP	Spatial compromise aggregation	Designed for raster-based environments	Requires careful scaling and parameter selection	Middle stage: spatial compromise mapping

4.3. Outranking Methods

Outranking techniques evaluate alternatives through pairwise comparisons to establish dominance or preference relationships rather than to generate a single aggregated score. Unlike fully compensatory methods, outranking approaches allow partial or non-compensatory decision processes, making them suitable where weak performance in one criterion should not be offset by stronger performance in another [58,59].

The ELimination Et Choix Traduisant la REalité (ELECTRE) and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) families are among the most established methods in this category. ELECTRE uses concordance and discordance indices to determine whether one alternative outranks another while incorporating threshold parameters defining acceptable differences among criteria [58,60]. PROMETHEE applies preference functions and net-flow calculations to produce rankings with relatively intuitive interpretation [61,62].

Despite their methodological strengths, these techniques are less common in EO-supported heritage applications due to their implementation complexity and limited compatibility with continuous raster analysis. Applications generally require specifying several parameters, including thresholds and preference functions, which may introduce additional subjectivity. Furthermore, these methods are often more suitable for discrete alternatives than extensive raster datasets [13,54].

Therefore, outranking methods are more frequently applied to scenario comparison, policy evaluation, or alternative planning exercises than to continuous susceptibility mapping (Table 4). Although they reduce compensation effects across criteria, broader implementation of EO-supported cultural heritage assessment remains limited.

Table 4. Outranking MCDA methods.

Method	Primary Role	Main Advantage	Main Limitation	Typical Use in EO/GIS Workflow
ELECTRE	Pairwise dominance analysis	Handles conflicting criteria; non-compensatory	Complex; threshold-dependent, difficult raster implementation	Discrete spatial alternatives or planning scenarios
PROMETHEE	Preference-based ranking	Flexible preference modeling; clear ranking structure	Subjective preference functions; limited GIS compatibility	Scenario comparison and alternative evaluation

4.4. Utility-Based Methods

Utility-based techniques originate in classical decision theory and represent decision-maker preferences through explicit utility functions that describe trade-offs among criteria. These methods assign utility values to alternatives and aggregate them into measures of overall preference [63].

Multi-Attribute Utility Theory (MAUT) and the Simple Multi-Attribute Rating Technique (SMART) are among the most representative methods within this category. MAUT provides a basis for modeling preferences under uncertainty while incorporating probabilistic information and complex trade-off relationships. SMART represents a simplified variation relying on direct scoring and weighting procedures [64].

Despite their conceptual basis, utility-based techniques are less frequently used in GIS and EO-supported analyses. Their implementation often requires detailed specification of utility functions and preference structures, which can be difficult to define in complex spatial environments. These methods are also less compatible with raster workflows involving large numbers of spatial units.

As a result, utility-based methods (Table 5) are often used in conceptual analyses or relatively small decision problems rather than operational geospatial workflows. In cultural heritage assessment, direct implementation remains limited, although its underlying principles continue to influence hybrid analytical methods.

Table 5. Utility-based MCDA methods.

Method	Primary Role	Main Advantage	Main Limitation	Typical Use in EO/GIS Workflow
MAUT	Preference modeling through utility functions	Strong theoretical foundation; handles trade-offs explicitly	Difficult utility elicitation; low spatial applicability	Conceptual framework; small-scale decision problems
SMART	Simplified preference scoring	Simple, transparent, easy to apply	Oversimplified; limited uncertainty handling; non-spatial	Preliminary evaluation of alternatives

4.5. Uncertainty-Aware MCDA Methods

Uncertainty-aware techniques address the vagueness, incompleteness, and inconsistency commonly encountered in environmental and geospatial analyses. Within EO-supported applications, uncertainty may arise from sensor limitations, differences in spatial resolution, environmental fluctuations, and subjective judgment. Explicit treatment of these sources of variability has therefore received growing attention in spatial decision analysis [55,65].

Among commonly used methods, fuzzy MCDA incorporates fuzzy-set theory to represent imprecise or linguistic information through membership functions, allowing gradual transitions between classes rather than fixed thresholds [66–68]. Such characteristics make fuzzy approaches suitable where environmental indicators or expert-derived information remain ambiguous.

Dempster–Shafer Theory (DST) provides an alternative evidential reasoning approach capable of combining information sources while representing conflict and incompleteness through belief and plausibility measures [69,70]. In geospatial analyses, DST has been used in hazard susceptibility studies where EO-derived indicators differ in reliability or completeness [71].

These methods also introduce additional methodological demands. Fuzzy approaches require careful specification of membership functions, whereas evidential techniques, such as DST, can be computationally demanding and sensitive to assumptions. Integration within conventional GIS workflows may therefore be less straightforward.

Despite these constraints, uncertainty-aware techniques (Table 6) contribute to more defensible spatial analyses by explicitly representing ambiguity and variability. In cultural heritage contexts, where incomplete documentation and heterogeneous information are common, these methods may improve the interpretation of risk assessments.

Table 6. Uncertainty-aware MCDA methods.

Method	Primary Role	Main Advantage	Main Limitation	Typical Use in EO/GIS Workflow
Fuzzy MCDA	Modeling vagueness and imprecision	Handles linguistic and uncertain inputs; flexible	Subjective membership functions	Middle stage: fuzzification and integration of EO indicators
DST	Evidence fusion under uncertainty	Explicit modeling of conflict and incompleteness	Computational complexity; sensitive to belief assignment	Middle/late stage: multi-source data integration

4.6. Data-Driven and Machine Learning Methods for Spatial Susceptibility

Data-driven and machine-learning (ML) methods are widely used in geospatial analyses to model nonlinear relationships between environmental predictors and observed

phenomena. In GIS and EO applications, these methods are commonly used for susceptibility and hazard mapping because they can process large, heterogeneous datasets and achieve high classification accuracy [71,72].

Common techniques include Random Forest (RF), Support Vector Machines (SVM), and Convolutional Neural Networks (CNN). Random Forest combines multiple decision trees to reduce sensitivity to noise and improve classification consistency [73]. SVM identifies separating boundaries within high-dimensional feature spaces and often performs well with limited training datasets [74]. CNNs extract hierarchical spatial patterns from high-resolution imagery, making them effective for feature recognition and EO image analysis [75].

Unlike MCDA methods, machine-learning techniques primarily focus on prediction rather than structured decision-making. Consequently, they are generally better suited to generating susceptibility indicators than to explicitly representing stakeholder preferences, trade-offs, or management priorities. In addition, many machine-learning techniques remain difficult to interpret because the models' decision processes are not always transparent.

For this reason, machine-learning methods are increasingly combined with MCDA within hybrid workflows. In these cases, machine-learning outputs generate predictive indicators or susceptibility layers that are later incorporated into decision-analysis procedures [72,76]. Such combinations attempt to merge predictive capacity with more interpretable evaluation processes.

In cultural heritage applications, hybrid machine-learning MCDA workflows may facilitate the integration of EO-derived indicators alongside expert knowledge and management priorities. Nevertheless, challenges associated with interpretability, data requirements, and integration into reproducible workflows continue to limit broader implementation. The characteristics, advantages, limitations, and typical EO/GIS roles of these data-driven and machine-learning methods are summarized in Table 7.

Table 7. Data-driven and machine-learning methods.

Method	Primary Role	Main Advantage	Main Limitation	Typical Use in EO/GIS Workflow
Random Forest	Susceptibility prediction	High accuracy; robust to noise	Limited interpretability (black-box)	Early–middle stage: generate susceptibility layers
SVM	Spatial classification	Effective with limited training data	Parameter tuning; limited interpretability	Early–middle stage: classification and modeling
CNN	Image-based prediction	Captures spatial patterns; high performance	Data-intensive; low transparency	Early stage: EO image analysis and feature extraction

4.7. Supporting Frameworks

Several complementary techniques are incorporated into MCDA workflows to examine uncertainty, reduce subjectivity, and refine the selection of criteria. Although these methods do not represent standalone MCDA approaches, they contribute to weighting procedures, dimensionality reduction, and sensitivity evaluation within geospatial analyses [12,13,50].

The Delphi method is frequently used for structured expert elicitation, contributing to consensus-building during criterion definition and weighting [77]. Entropy weighting can derive criterion importance from dataset characteristics and may reduce dependence on subjective judgment [78]. Principal Component Analysis (PCA) can support criteria refinement by identifying correlated variables and reducing redundancy, although it is not

itself an MCDA weighting method [79]. Decision-Making Trial and Evaluation Laboratory (DEMATEL) additionally examines causal relationships among criteria, helping identify interdependencies within complex systems [80].

Sensitivity analysis and simulation-based procedures are commonly used to evaluate variability in MCDA outputs. Within spatial applications, Spatial Monte Carlo Analysis (SMCA) propagates variability through datasets to examine output stability under changing assumptions [13]. Such methods are particularly relevant in EO-supported analyses, where differences in data quality and model assumptions may strongly influence results.

These complementary techniques (Table 8) support criteria refinement and the systematic examination of variability, contributing to more reproducible MCDA workflows. In cultural heritage studies, where incomplete information and heterogeneous datasets are common, their integration may strengthen the interpretation of analytical outcomes.

Table 8. Complementary methods for criteria refinement and uncertainty evaluation.

Method	Primary Role	Main Advantage	Main Limitation	Typical Use in EO/GIS Workflow
Delphi	Expert consensus	Reduces individual bias; structured elicitation	Time-consuming	Early stage: criteria definition and validation
Entropy weighting	Objective weight derivation	Data-driven; reproducible	Sensitive to data quality	Early stage: weight calibration
PCA	Dimensionality reduction	Handles correlated variables	Reduced interpretability	Pre-processing of EO indicators
DEMATEL	Causal relationship analysis	Identifies key drivers and interdependencies	Not a ranking method	Model structuring and system analysis
SMCA	Uncertainty and robustness analysis	Quantifies variability and stability	Computational cost	Late stage: sensitivity and robustness analysis

Not all reviewed methods are equally suitable for EO-supported cultural heritage applications. Weighting-based approaches, particularly AHP and WLC, combined with uncertainty-aware extensions, currently offer broad applicability because of their compatibility with raster analyses and relatively straightforward implementation. By contrast, outranking and utility-based methods are generally less suited to large raster datasets.

5. Strengths and Limitations of MCDA Approaches

Multi-Criteria Decision Analysis is widely applied to problems involving multiple, potentially conflicting criteria. Its capacity to combine quantitative indicators, qualitative information, and stakeholder perspectives has supported its use across environmental management, land-use planning, and hazard assessment [12,27,81]. When integrated with GIS and EO datasets, MCDA enables spatially explicit assessments of suitability, vulnerability, and risk. However, its results remain sensitive to the weighting of criteria, aggregation behavior, uncertainty treatment, and spatial implementation.

5.1. Criteria Weighting and Subjectivity

Criteria weighting is one of the most influential components of MCDA because it determines the relative importance of each criterion in the final evaluation. In many studies, weights are derived from expert judgment or stakeholder input using methods such as AHP [51,54]. This procedure allows for the incorporation of contextual knowledge, domain expertise, and stakeholder priorities into analytical models.

Expert-driven weighting offers advantages because it captures considerations that may not be derived solely from empirical data. Participatory approaches can broaden the representation of stakeholder perspectives in evaluation processes [20,25]. This aspect becomes particularly relevant in cultural heritage assessment, where environmental indicators often interact with social, cultural, and historical dimensions.

At the same time, reliance on expert judgment introduces subjectivity, potentially affecting consistency and reproducibility. Different experts or stakeholder groups may assign substantially different levels of importance to identical criteria, leading to variation in analytical outputs. Even relatively small modifications in weighting schemes can alter rankings or spatial results, illustrating the sensitivity of MCDA outcomes to subjective inputs [15,21,82].

Data-driven weighting can complement expert judgment. Entropy-based methods derive importance from dataset characteristics [78], while PCA can identify correlated variables and reduce redundancy [79]. Hybrid approaches may balance contextual knowledge and empirical evidence [27,65].

5.2. Aggregation Strategies and Compensation Effects

Aggregation is a critical stage in MCDA because it determines how individual criteria are combined into a single evaluation measure. Widely used techniques, including SAW and WLC, rely on additive aggregation procedures in which weighted criteria are summed to generate composite outputs [50,83]. These methods are computationally efficient, relatively straightforward to interpret, and compatible with GIS-based analyses. However, their compensatory structure may be unsuitable for risk assessment, where critical thresholds or vulnerabilities should not be offset.

To reduce these effects, non-compensatory or partially compensatory approaches may be used. Outranking methods such as ELECTRE and PROMETHEE can prevent strong performance on one criterion from fully offsetting unacceptable performance on another [58–62]. OWA provides a different aggregation mechanism by allowing the levels of compensation and decision risk to be adjusted through its order weights [13,53]. Their implementation, however, often requires additional parameter specification and remains less common in large raster environments.

In cultural heritage assessment, aggregation choices influence how interactions among risks are represented and may determine whether critical vulnerabilities remain visible or are masked. Consequently, selecting aggregation procedures requires careful consideration, and comparing multiple methods may be necessary when multi-threat conditions are present.

5.3. Uncertainty Representation and Propagation

Uncertainty is inherent in geospatial analyses, particularly in EO-supported applications, where data quality, temporal coverage, and spatial resolution may vary considerably. In MCDA, variability may originate from measurement errors, incomplete datasets, subjective judgment, or assumptions embedded within analytical procedures [15,65,82].

Many conventional MCDA methods treat input data and weighting values as deterministic, potentially producing overconfident interpretations. This issue becomes especially relevant in cultural heritage studies, where incomplete documentation, inconsistent definitions of vulnerability, and intangible values introduce additional ambiguity [6,7].

Several techniques have been developed to address these issues. Fuzzy MCDA represents imprecise information through membership functions [66–68], while Dempster–Shafer Theory combines information sources with differing reliability levels [69,70]. Sensitivity analysis and simulation-based procedures, including Monte Carlo methods, are also frequently used to assess the stability of results under varying assumptions [21].

Although these developments improve the representation of ambiguity within analytical workflows, implementation remains challenging. Computational demands increase, and communicating variability to decision-makers is often difficult. Nevertheless, explicit treatment of uncertainty remains necessary for interpreting EO-supported analyses conducted under incomplete or variable conditions.

5.4. Spatial Implementation Challenges

GIS-based procedures enable environmental, topographic, and socio-economic datasets to be combined into geographically explicit outputs [14,50]. This capability is particularly relevant for EO-supported studies, where large volumes of environmental information can be analyzed efficiently.

Several methodological and technical issues remain. One concern is data heterogeneity, as EO datasets often differ in spatial resolution, temporal coverage, and overall quality. Combining such datasets often requires preprocessing operations, including re-sampling and normalization, which may introduce additional variability or modify spatial relationships [84].

Spatial autocorrelation and scale dependency further complicate matters. Many MCDA techniques assume independence among criteria and spatial units, whereas environmental variables commonly exhibit strong geographic relationships. Differences in scale between satellite imagery, digital elevation models, and administrative boundaries may also influence the interpretation of analytical outcomes [85].

Computational demands increase when advanced MCDA techniques, uncertainty analysis, or hybrid procedures are applied to high-resolution raster datasets. Simpler aggregation methods remain comparatively efficient, whereas more complex workflows may require substantial processing resources.

The principal methodological issues associated with MCDA applications, together with commonly used mitigation strategies, are summarised in Table 9.

Table 9. Key methodological challenges in MCDA and mitigation strategies.

Methodological Issue	Strength	Limitation	Mitigation Strategy	EO/GIS Relevance
Criteria weighting and subjectivity	Allows incorporation of expert knowledge, stakeholder preferences, and contextual priorities into decision models	Weight assignment may be subjective and inconsistent across experts, potentially affecting the reproducibility of results.	Delphi method, entropy weighting, PCA-based criteria reduction, hybrid subjective-objective weighting approaches	Important for integrating expert knowledge with EO-derived indicators in spatial decision-support models
Aggregation strategies and compensation effects	Additive aggregation methods are transparent, computationally efficient, and easy to implement in GIS environments	Full compensation behavior may allow poor performance in critical criteria to be offset by high scores in other criteria	Outranking methods (ELECTRE, PROMETHEE), Ordered Weighted Averaging (OWA), and compromise programming	Useful when modeling risk-sensitive spatial decisions where certain criteria should not be compensated
Uncertainty representation and propagation	MCDA provides structured frameworks for combining heterogeneous data and expert judgment	Many traditional MCDA methods assume deterministic inputs and do not explicitly represent uncertainty	Fuzzy MCDA, Dempster-Shafer Theory, Monte Carlo simulation, sensitivity analysis	Enhances robustness of EO-based hazard and vulnerability assessments
Spatial implementation challenges	GIS integration enables spatially explicit evaluation of environmental and socio-economic criteria	Data heterogeneity, scale mismatch, spatial autocorrelation, and computational complexity may affect results	GIS-based MCDA workflows, spatial sensitivity analysis, hybrid ML-MCDA models	Critical for integrating EO datasets, spatial indicators, and environmental models

6. Synthesis

6.1. Overall Findings

Multi-Criteria Decision Analysis has traditionally been used for decision problems involving multiple, often conflicting criteria. As noted by Velasquez and Hester [54] and Cinelli et al. [12], many foundational MCDA methods were originally developed in operations research and decision theory to support structured decision-making under well-defined conditions. These methods relied primarily on expert judgment, rule-based aggregation procedures, and limited representation of uncertainty.

As MCDA expanded into environmental and spatial applications, its methodological requirements also changed. Pelissari et al. [65] emphasize the need to account for uncertainty arising from incomplete information, variable data, and subjective judgment. Malczewski and Rinner [13] demonstrate how integrating GIS extends MCDA to spatial decision support, while Le Cozannet et al. [23] show how repeated EO observations can support environmental monitoring and disaster-risk management. In cultural heritage, GIS and remote sensing have been applied to site management and monitoring [41,47], while recent studies illustrate the growing use of open-access EO data for heritage threat assessment [48,49]. Figure 2 summarises the transition from deterministic methods to integrated, uncertainty-aware EO/GIS analytical procedures.

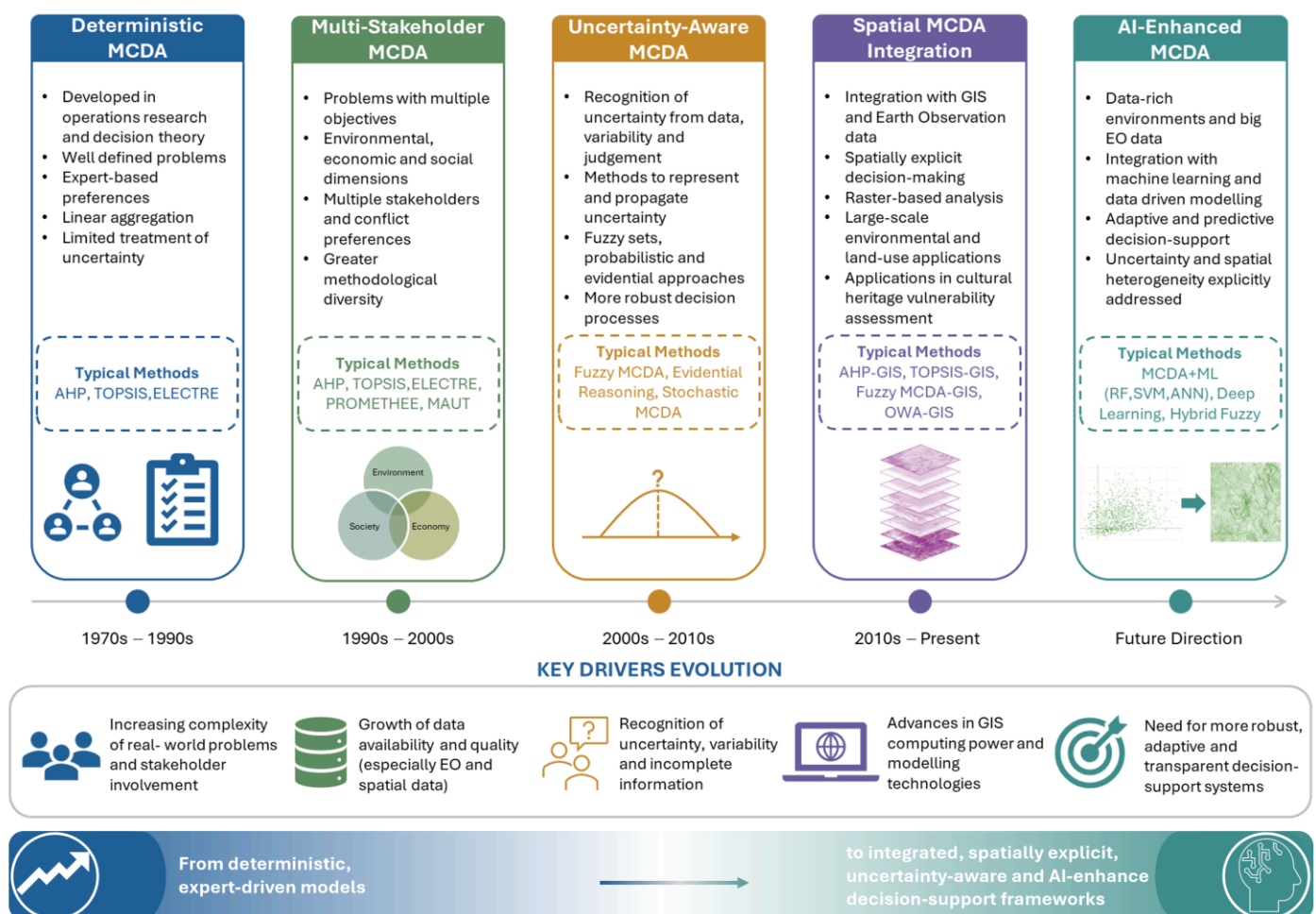


Figure 2. Evolution of MCDA from deterministic methods to integrated EO/GIS-based, uncertainty-aware, and hybrid decision-support frameworks.

This development should not be interpreted as a complete replacement of conventional methods. Rather, it represents a gradual expansion from static, expert-based assessments toward workflows that can incorporate temporal observations, alternative weighting scenarios, uncertainty evaluation, stakeholder preferences, and data-driven evidence.

The reviewed studies show that weighting-based methods remain prominent. Mardani et al. [27] confirm their broad adoption across different application domains, while Malczewski [50] explains their suitability for GIS-based analysis. Their compatibility with raster data, transparent structure, and relatively straightforward implementation partly explain the continued prominence of AHP combined with weighted overlay. A trade-off emerges across the reviewed literature between methodological simplicity and analytical robustness. Simpler approaches are easier to implement and communicate, whereas uncertainty-aware and hybrid methods require additional data, expertise, and computational resources.

Regarding the research questions, four principal findings emerge. First, MCDA has evolved from primarily deterministic and expert-based procedures to spatially explicit, uncertainty-aware, and hybrid approaches. This development is reflected in the spatial review by Malczewski [50], the uncertainty synthesis by Pelissari et al. [65], and the data-driven review by Liao et al. [72]. Second, weighting-based approaches, particularly AHP combined with GIS-based weighted overlay, remain prominent. Mardani et al. [27] identify their broad adoption, while Dammag et al. [32], Michaelides and Agapiou [42], and Nicu [43] illustrate their use in heritage-related assessment. Third, recurring methodological limitations include subjective weighting, compensatory aggregation, limited treatment of uncertainty, static use of EO indicators, insufficient validation, single-threat analysis, and incomplete stakeholder participation. Similar concerns are reported by Crowley et al. [6], Feizizadeh and Blaschke [15], and Bosher et al. [38]. Fourth, integrated workflows can strengthen cultural heritage risk assessment under multi-threat conditions by combining GIS-based spatial analysis, repeatable environmental observations from EO, transparent decision structuring through MCDA, and sensitivity or uncertainty analysis, as illustrated by Ravankhah et al. [1], Appiotti et al. [28], Borges et al. [29], and Hochrainer-Stigler et al. [86]. Nevertheless, the appropriate combination depends on the heritage context, available evidence, intended users, and management decisions.

Potential users include heritage authorities, site managers, municipalities, civil-protection agencies, conservation professionals, spatial planners, and research institutions. These users may apply MCDA outputs to identify exposed assets, prioritize inspections and interventions, compare management alternatives, support preparedness, and allocate resources. Although open-access EO data and GIS software can reduce financial barriers, implementation still requires expertise, field validation, stakeholder consultation, data management, training, and periodic updates. UNESCO guidance [87] also emphasize the importance of identifying affected heritage values, considering alternatives, and involving relevant institutions and stakeholders.

Institutional responsibilities and funding determine whether analytical outputs lead to practical action. A risk map has limited operational value if no organization is responsible for interpreting it, updating it, or funding the recommended interventions. Implementation planning should therefore identify the intended users, available resources, data responsibilities, update requirements, and the process for translating priorities into conservation measures. MCDA outputs should support professional and community judgment rather than replace it.

6.2. Future Directions

A persistent issue across heritage studies is the continued reliance on weighting-based methods, particularly AHP, while alternative decision-analysis techniques receive comparatively less attention. Although AHP provides a practical and accessible procedure, its repeated use without comparison with alternative methods may oversimplify interactions among criteria, especially when interdependencies and uncertainty are not explicitly examined.

The treatment of uncertainty also remains inconsistent across published applications. Methods including fuzzy MCDA, sensitivity analysis, and evidential reasoning are available but are not consistently incorporated into heritage-risk workflows. Transferable techniques from related fields include sampling-based uncertainty propagation, examined by Hajihassanpour et al. [88], and Bayesian inference, used by Tomar et al. [89] to update damage and restoration forecasts as new evidence becomes available.

EO-derived indicators are similarly underused for temporal analysis. Although remote sensing data are increasingly incorporated into risk assessment, they are often represented as static environmental layers. Van Westen [90] demonstrates the broader contribution of remote sensing and GIS to natural-hazard assessment, while Stewart et al. [91] show how MCDA can be combined with scenario planning. These approaches enable the integration of EO time series, scenario analysis, and historical event inventories, allowing heritage-risk assessments to be updated as conditions change.

The representation of stakeholder perspectives and intangible cultural values remains another challenge. Participation is often limited to criteria selection or weighting rather than being incorporated throughout the assessment. Arrighi et al. [92], for example, demonstrate how social value and participatory processes can help prioritize cultural heritage risks. Future workflows should therefore involve stakeholders in defining the problem, interpreting the results, and evaluating possible interventions.

Multi-threat assessment also requires further development. Cultural heritage may be affected simultaneously by floods, landslides, coastal erosion, wildfire, climate variability, and human pressures, but these threats are often assessed separately. Bhunia and Shit [93] demonstrate the contribution of geospatial technologies to multi-hazard assessment, while Ward et al. [94] emphasize the need for broader pathways linking multi-hazard analysis to disaster risk management.

More standardized and transparent workflows are also needed. These should document data sources, preprocessing, criterion selection, weighting, aggregation, uncertainty analysis, validation, and updating procedures. Update schedules should align with the rate of change of the monitored process and the intended management purpose. Near-real-time processing is most relevant for rapidly changing conditions and post-event assessment, whereas relatively stable variables, such as terrain and geology, may require less frequent revision. More dynamic indicators, including vegetation, moisture, shoreline position, ground deformation, and damage, may require seasonal or event-driven updates [23,29,30].

Hybrid approaches combining MCDA, EO, uncertainty analysis, and machine learning offer opportunities for more adaptive assessment. However, greater methodological complexity does not automatically produce better decisions. Liao et al. [72] emphasize the predictive potential of data-driven methods, while Bakhtiari et al. [95] demonstrate the potential of dynamic Bayesian networks for temporal multi-hazard assessment. The value of such approaches should be demonstrated through transparent validation and sensitivity analysis rather than assumed from their complexity. Table 10 summarises the principal methodological gaps and corresponding research priorities.

Table 10. Methodological gaps in MCDA applications for cultural heritage assessment and future research directions.

Identified Gap	Potential Effect	Current Situation	Possible Direction
Heavy reliance on AHP	Limited representation of interactions among criteria	Predominant reliance on expert-derived weighting	Hybrid weighting approaches
Limited uncertainty treatment	Reduced confidence in output robustness	Uncertainty is not consistently evaluated	Fuzzy MCDA, sensitivity analysis, and Monte Carlo simulation
Predominantly static use of EO indicators	Limited representation of change over time	EO-derived indicators are often represented as fixed layers	EO time series and change detection
Single threat assessments	Missed hazard interactions and cascading effects	Hazards are generally evaluated separately	Multi-threat frameworks
Limited participatory methods	Incomplete representation of social and intangible values	Stakeholder input is generally restricted to criteria selection or weighting	Stakeholder involvement throughout the assessment
Limited use of historical event data	Reduced empirical support	Historical events are not consistently used for calibration or validation	Historical-event inventories for calibration and validation
Fragmented hybrid methods	Low reproducibility	Hybrid methods generally follow case-specific workflows	Standardized reporting and validation workflows

7. Conclusions

This review examined the evolution, application domains, and methodological challenges of MCDA in geospatial decision analysis, with particular attention to cultural heritage risk assessment using GIS and EO data. MCDA provides a structured approach to integrating heterogeneous datasets, environmental indicators, expert knowledge, stakeholder priorities, and qualitative information. When combined with GIS, it enables spatially explicit assessment, while EO data provide repeatable observations of environmental conditions and landscape change.

The analysis also indicates clear methodological patterns. Weighting-based methods, particularly AHP combined with GIS overlay procedures, remain prominent because of their accessibility, interpretability, and compatibility with raster data. However, extensive reliance on these approaches may oversimplify interactions among criteria and provide limited treatment of uncertainty. Temporal EO information, multi-threat interactions, validation, stakeholder perspectives, and intangible cultural values also remain insufficiently represented in many heritage applications. Hybrid and data-driven approaches can expand analytical capabilities, but greater complexity does not automatically produce more reliable or operationally useful results. Consequently, no single MCDA method is appropriate for every heritage context.

The reviewed applications are principally documented in academic studies, research projects, and decision-support frameworks. Their intended or potential users include heritage authorities, site managers, municipalities, civil protection agencies, conservation professionals, spatial planners, and research institutions. Potential uses include identifying exposed heritage assets, prioritizing inspections and interventions, comparing management alternatives, and supporting preparedness and resource allocation. Regional GIS-based models can identify broader spatial priorities, whereas detailed asset-level models can incorporate structural condition, cultural significance, and management requirements. These applications should therefore be considered complementary rather than interchangeable.

The findings suggest that progress in cultural heritage risk assessment may depend less on adding new analytical methods than on appropriately selecting and combining existing approaches. More useful workflows will integrate temporal EO information, uncertainty and sensitivity analyses, multi-threat relationships, validation, and stakeholder knowledge

according to the decision context. Operational implementation also requires clearly defined institutional responsibilities, appropriate expertise and resources, and update schedules commensurate with the monitored threats. MCDA, GIS, and EO should therefore be treated as decision-support tools that complement professional expertise, institutional knowledge, and community judgment.

Author Contributions: Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, and visualization, K.M. and A.A.; supervision, A.A.; funding acquisition, A.A. All authors have read and agreed to the published version of the manuscript.

Funding: This work has been supported by the ARGUS EU project (Grant Agreement No. 101132308), funded by the European Union. The views and opinions expressed are, however, those of the author(s) only and do not necessarily reflect those of the European Union or of the European Research Executive Agency (REA); neither the European Union nor the granting authority can be held responsible for them.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: This research forms part of the thesis of K.M., conducted at the EOcult: Earth Observation Cultural Heritage Lab (<https://web.cut.ac.cy/eocult/>, accessed on 6 June 2026), Department of Civil Engineering and Geomatics, Cyprus University of Technology. The authors acknowledge the use of language-editing tools (Grammarly, 2026) and AI-based assistants (ChatGPT, version GPT-5 by OpenAI) to polish language and improve clarity. All AI-generated suggestions were carefully reviewed and edited by the authors, who take full responsibility for the scientific content, interpretation, and conclusions presented in this manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANP	Analytic Network Process
CNN	Convolutional Neural Networks
DST	Dempster–Shafer Theory
EO	Earth Observation
GIS	Geographic Information Systems
MAUT	Multi-Attribute Utility Theory
MCDA	Multi-Criteria Decision Analysis
ML	Machine Learning
OWA	Ordered Weighted Averaging
PCA	Principal Component Analysis
RF	Random Forest
SAW	Simple Additive Weighting
SCP	Spatial Compromise Programming
SMART	Simple Multi-Attribute Rating Technique
SMCA	Spatial Monte Carlo Analysis
SVM	Support Vector Machines
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
UNESCO	United Nations Educational, Scientific and Cultural Organization
WLC	Weighted Linear Combination

References

1. Ravankhah, M.; de Wit, R.; Argyriou, A.V.; Chliaoutakis, A.; Revez, M.J.; Birkmann, J.; Žuvela-Aloise, M.; Sarris, A.; Tzigounaki, A.; Giapitsoglou, K. Integrated Assessment of Natural Hazards, Including Climate Change's Influences, for Cultural Heritage Sites: The Case of the Historic Centre of Rethymno in Greece. *Int. J. Disaster Risk Sci.* **2019**, *10*, 343–361. [\[CrossRef\]](#)
2. Falk, M.; Hagsten, E. A management perspective on threats to Cultural World Heritage Sites. *Int. J. Herit. Stud.* **2023**, *29*, 167–183. [\[CrossRef\]](#)
3. Valagussa, A.; Frattini, P.; Crosta, G.; Spizzichino, D.; Leoni, G.; Margottini, C. Multi-risk analysis on European cultural and natural UNESCO heritage sites. *Nat. Hazards* **2020**, *105*, 2659–2676. [\[CrossRef\]](#)
4. UNESCO. *Managing Disaster Risks for World Heritage*; World Heritage Resource Manual; United Nations Educational, Scientific and Cultural Organization (UNESCO): Paris, France, 2010; p. 69.
5. Fatorić, S.; Seekamp, E. Are cultural heritage and resources threatened by climate change? A systematic literature review. *Clim. Change* **2017**, *142*, 227–254. [\[CrossRef\]](#)
6. Crowley, K.; Jackson, R.; O'Connell, S.; Karunarthna, D.; Anantasari, E.; Retnowati, A.; Niemand, D. Cultural heritage and risk assessments: Gaps, challenges, and future research directions for the inclusion of heritage within climate change adaptation and disaster management. *Clim. Resil. Sustain.* **2022**, *1*, e45. [\[CrossRef\]](#)
7. Ramalhinho, A.R.; Macedo, M.F. Cultural heritage risk analysis models: An overview. *Int. J. Conserv. Sci.* **2019**, *10*, 39–58.
8. Malczewski, J.; Jankowski, P. Emerging trends and research frontiers in spatial multicriteria analysis. *Int. J. Geogr. Inf. Sci.* **2020**, *34*, 1257–1282. [\[CrossRef\]](#)
9. Cuca, B.; Zaina, F.; Tapete, D. Monitoring of Damages to Cultural Heritage across Europe Using Remote Sensing and Earth Observation: Assessment of Scientific and Grey Literature. *Remote Sens.* **2023**, *15*, 3748. [\[CrossRef\]](#)
10. UNESCO. *Policy Document on Climate Action for World Heritage*; Document WHC/23/24.GA/INF.8; UNESCO World Heritage Centre: Paris, France, 2023.
11. UNESCO. *Policy for the Integration of a Sustainable Development Perspective into the Processes of the World Heritage Convention*; UNESCO World Heritage Centre: Paris, France, 2015.
12. Cinelli, M.; Kadziński, M.; Gonzalez, M.; Słowiński, R. How to support the application of multiple criteria decision analysis? Let us start with a comprehensive taxonomy. *Omega* **2020**, *96*, 102261. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Malczewski, J.; Rinner, C. Web-Based and Mobile GIS-MCDA. In *Multicriteria Decision Analysis in Geographic Information Science*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 311–324. [\[CrossRef\]](#)
14. Greene, R.; Devillers, R.; Luther, J.E.; Eddy, B.G. GIS-Based Multiple-Criteria Decision Analysis. *Geogr. Compass* **2011**, *5*, 412–432. [\[CrossRef\]](#)
15. Feizizadeh, B.; Blaschke, T. An uncertainty and sensitivity analysis approach for GIS-based multicriteria landslide susceptibility mapping. *Int. J. Geogr. Inf. Sci.* **2014**, *28*, 610–638. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Kiker, G.A.; Bridges, T.S.; Varghese, A.; Seager, P.T.; Linkov, I. Application of multicriteria decision analysis in environmental decision-making. *Integr. Environ. Assess. Manag.* **2005**, *1*, 95–108. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Havranek, T.J. Multi-criteria decision analysis for environmental remediation: Benefits, challenges, and recommended practices. *Remediat. J.* **2019**, *29*, 93–108. [\[CrossRef\]](#)
18. Abrams, F.; Hendrickx, L.; Turcanu, C.; Sweeck, L.; Van Orshoven, J. Multi-Criteria Decision Analysis to Support the Remediation of Polluted Soils: A Review of Case Studies. *Land* **2024**, *13*, 887. [\[CrossRef\]](#)
19. Adem Esmail, B.; Geneletti, D. Multi-criteria decision analysis for nature conservation: A review of 20 years of applications. *Methods Ecol. Evol.* **2018**, *9*, 42–53. [\[CrossRef\]](#)
20. Estévez, R.A.; Gelcich, S. Participative multi-criteria decision analysis in marine management and conservation: Research progress and the challenge of integrating value judgments and uncertainty. *Mar. Policy* **2015**, *61*, 1–7. [\[CrossRef\]](#)
21. Feizizadeh, B.; Jankowski, P.; Blaschke, T. A GIS based spatially-explicit sensitivity and uncertainty analysis approach for multi-criteria decision analysis. *Comput. Geosci.* **2014**, *64*, 81–95. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Shokati, B.; Feizizadeh, B. Sensitivity and uncertainty analysis of agro-ecological modeling for saffron plant cultivation using GIS spatial decision-making methods. *J. Environ. Plan. Manag.* **2018**, *62*, 517–533. [\[CrossRef\]](#)
23. Le Cozannet, G.; Kervyn, M.; Russo, S.; Speranza, C.I.; Ferrier, P.; Fournel, M.; Lopez, T.; Modaresi, H. Space-Based Earth Observations for Disaster Risk Management. *Surv. Geophys.* **2020**, *41*, 1209–1235. [\[CrossRef\]](#)
24. Lami, I.M.; Bottero, M.; Abastante, F. Multiple Criteria Decision Analysis to Assess Urban and Territorial Transformations: Insights from Practical Applications. In *Strategic Decision Making for Sustainable Management of Industrial Networks*; Springer: Cham, Switzerland, 2021; pp. 93–117. [\[CrossRef\]](#)
25. Chen, O.; Han, D. A Participatory Multiple Criteria Decision Analysis to Tackle a Complex Environmental Problem Involving Cultural Water Heritage and Nature. *Water* **2018**, *10*, 1785. [\[CrossRef\]](#)
26. Kim, J.-W.; Choi, H.-W.; Kim, S.-K.; Na, W.S. Review of Image-Processing-Based Technology for Structural Health Monitoring of Civil Infrastructures. *J. Imaging* **2024**, *10*, 93. [\[CrossRef\]](#) [\[PubMed\]](#)

27. Mardani, A.; Jusoh, A.; MD Nor, K.; Khalifah, Z.; Zakwan, N.; Valipour, A. Multiple criteria decision-making techniques and their applications—A review of the literature from 2000 to 2014. *Econ. Res.-Ekon. Istraž.* **2015**, *28*, 516–571. [\[CrossRef\]](#)
28. Appiotti, F.; Assumma, V.; Bottero, M.; Campostrini, P.; Datola, G.; Lombardi, P.; Rinaldi, E. Definition of a Risk Assessment Model within a European Interoperable Database Platform (EID) for Cultural Heritage. *J. Cult. Herit.* **2020**, *46*, 268–277. [\[CrossRef\]](#)
29. Borges, D.E.; Ramage, S.; Green, D.; Justice, C.; Nakalembe, C.; Whitcraft, A.; Barker, B.; Becker-Reshef, I.; Balagizi, C.; Salvi, S.; et al. Earth observations into action: The systemic integration of earth observation applications into national risk reduction decision structures. *Disaster Prev. Manag. Int. J.* **2023**, *32*, 163–185. [\[CrossRef\]](#)
30. Li, B.; Gong, A.; Liu, L.; Li, J.; Li, J.; Li, L.; Pan, X.; Chen, Z. An Earth Observation Framework in Service of the Sendai Framework for Disaster Risk Reduction 2015–2030. *ISPRS Int. J. Geo-Inf.* **2023**, *12*, 232. [\[CrossRef\]](#)
31. Briz, E.; Garmendia, L.; Quesada-Ganuza, L.; Villaverde, A.; Alvarez, I.; Egusquiza, A. Prioritization Methodology for Resilience Enhancement of Historic Areas Facing Climate Change-Related Hazards. In *The Future of Heritage Science and Technologies*; Springer: Cham, Switzerland, 2022; pp. 3–14. [\[CrossRef\]](#)
32. Qasim Derhem Dammag, B.; Jian, D.; Dammag, A.Q. Cultural Heritage Sites Risk Assessment and Management Using a Hybridized Technique Based on GIS and SWOT-AHP in the Ancient City of Ibb, Yemen. *Int. J. Archit. Herit.* **2024**, *19*, 1537–1572. [\[CrossRef\]](#)
33. Alexandrakis, G.; De Vita, S.; Di Vito, M. Preliminary risk assessment at Ustica based on indicators of natural and human processes. *Ann. Geophys.* **2019**, *62*, VO07. [\[CrossRef\]](#)
34. Spiridon-Ursu, P.; Breabăn, I.-G.; Sandu, I.; Ursu, A. A GIS-based model for multicriteria assessment of architectural cultural heritage conservation status. *Present Environ. Sustain. Dev.* **2024**, *18*, 225–251. [\[CrossRef\]](#)
35. Ravan, M.; Revez, M.J.; Pinto, I.V.; Brum, P.; Birkmann, J. A Vulnerability Assessment Framework for Cultural Heritage Sites: The Case of the Roman Ruins of Tróia. *Int. J. Disaster Risk Sci.* **2023**, *14*, 26–40. [\[CrossRef\]](#)
36. Figueiredo, R.; Romão, X.; Paupério, E. A Multilevel Framework for Flood Risk Assessment of Cultural Heritage. In *Managing Disaster Risks to Cultural Heritage*; Routledge: London, UK, 2023; pp. 242–257. [\[CrossRef\]](#)
37. Mansir, D.; Kasim, N.; Mat Radzuan, I.S. An exploration of disaster risk to cultural heritage assets: Towards effective conservation. *Int. J. Conserv. Sci.* **2018**, *9*, 523–536.
38. Bosher, L.; Kim, D.; Okubo, T.; Chmutina, K.; Jigyasu, R. Dealing with multiple hazards and threats on cultural heritage sites: An assessment of 80 case studies. *Disaster Prev. Manag. Int. J.* **2019**, *29*, 109–128. [\[CrossRef\]](#)
39. Daly, C. A Framework for Assessing the Vulnerability of Archaeological Sites to Climate Change: Theory, Development, and Application. *Conserv. Manag. Archaeol. Sites* **2014**, *16*, 268–282. [\[CrossRef\]](#)
40. Giglio, F. Advanced Methodological Framework for Assessing Climate Change Impacts on Cultural Heritage Toward a Multi-scale Vulnerability Index. In *Climatic and Structural Safety in Multi-Hazard Regime of Cultural and Natural Heritage*; Springer: Cham, Switzerland, 2026; pp. 136–149. [\[CrossRef\]](#)
41. Agapiou, A.; Lysandrou, V.; Alexakis, D.; Themistocleous, K.; Cuca, B.; Argyriou, A.V.; Sarris, A.; Hadjimitsis, D.G. Cultural heritage management and monitoring using remote sensing data and GIS: The case study of Paphos area, Cyprus. *Comput. Environ. Urban Syst.* **2015**, *54*, 230–239. [\[CrossRef\]](#)
42. Michaelides, K.; Agapiou, A. An Open-Access Remote Sensing and AHP–GIS Framework for Flood Susceptibility Assessment of Cultural Heritage. *Geomatics* **2026**, *6*, 23. [\[CrossRef\]](#)
43. Nicu, I.C. Application of analytic hierarchy process, frequency ratio, and statistical index to landslide susceptibility: An approach to endangered cultural heritage. *Environ. Earth Sci.* **2018**, *77*, 79. [\[CrossRef\]](#)
44. Ferretti, V.; Bottero, M.; Mondini, G. Decision making and cultural heritage: An application of the Multi-Attribute Value Theory for the reuse of historical buildings. *J. Cult. Herit.* **2014**, *15*, 644–655. [\[CrossRef\]](#)
45. Mulubrhan, F.; Mokhtar, A.A.; Muhammad, M. Comparative Analysis Between Fuzzy and Traditional Analytical Hierarchy Process. *MATEC Web Conf.* **2014**, *13*, 1006. [\[CrossRef\]](#)
46. Ashour, M.; Mahdiyar, A. A comprehensive state-of-the-art survey on the recent modified and hybrid analytic hierarchy process approaches. *Appl. Soft Comput.* **2024**, *150*, 111014. [\[CrossRef\]](#)
47. Agapiou, A. Remote sensing heritage in a petabyte-scale: Satellite data and heritage Earth Engine© applications. *Int. J. Digit. Earth* **2016**, *10*, 85–102. [\[CrossRef\]](#)
48. Michaelides, K.; Hadjipetrou, S.; Agapiou, A.; Sarris, A.; Klinkenberg, V.; Polidorou, M. Addressing Cultural Heritage Challenges: Applications of Open-Access Remote Sensing Datasets for Monitoring Threats. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2025**, *48*, 67–74. [\[CrossRef\]](#)
49. Duțu, A.S.; Osztrovszky, V.F.; Michaelides, K.; Agapiou, A. Monitoring Remote Archaeological Sites Through Open-Access Satellite Datasets Against Natural Hazards—Case Study: Delos. *Heritage* **2026**, *9*, 143. [\[CrossRef\]](#)
50. Malczewski, J. GIS-based multicriteria decision analysis: A survey of the literature. *Int. J. Geogr. Inf. Sci.* **2006**, *20*, 703–726. [\[CrossRef\]](#)
51. Saaty, T.L. Decision making with the analytic hierarchy process. *Int. J. Serv. Sci.* **2008**, *1*, 83–98. [\[CrossRef\]](#)

52. Saaty, T.L. *Fundamentals of Decision Making and Priority Theory with the Analytic Hierarchy Process*; RWS Publications: Pittsburgh, PA, USA, 1994.
53. Yager, R.R. On Ordered Weighted Averaging Aggregation Operators in Multi-Criteria Decision Making. *IEEE Trans. Syst. Man Cybern.* **1988**, *18*, 183–190. [\[CrossRef\]](#)
54. Velasquez, M.; Hester, P. An Analysis of Multi-Criteria Decision Making Methods. *Int. J. Oper. Res.* **2013**, *10*, 56–66. [\[CrossRef\]](#)
55. Cinelli, M.; Coles, S.R.; Kirwan, K. Analysis of the potentials of multi criteria decision analysis methods to conduct sustainability assessment. *Ecol. Indic.* **2014**, *46*, 138–148. [\[CrossRef\]](#)
56. Hwang, C.L.; Yoon, K. *Multiple Attribute Decision Making: Methods and Applications*; Springer: New York, NY, USA, 1981. [\[CrossRef\]](#)
57. Opricovic, S.; Tzeng, G.-H. Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *Eur. J. Oper. Res.* **2004**, *156*, 445–455. [\[CrossRef\]](#)
58. Roy, B. Classement et choix en présence de points de vue multiples. *Rev. Fr. d'Inform. Rech. Opér.* **1968**, *2*, 57–75. [\[CrossRef\]](#)
59. Greco, S.; Figueira, J.; Ehrgott, M. *Multiple Criteria Decision Analysis*; Springer: New York, NY, USA, 2016; Volume 233. [\[CrossRef\]](#)
60. Govindan, K.; Jepsen, M.B. ELECTRE: A comprehensive literature review on methodologies and applications. *Eur. J. Oper. Res.* **2016**, *250*, 1–29. [\[CrossRef\]](#)
61. Brans, J.P.; Vincke, P. Note—A Preference Ranking Organisation Method. *Manag. Sci.* **1985**, *31*, 647–656. [\[CrossRef\]](#)
62. Behzadian, M.; Kazemzadeh, R.B.; Albadvi, A.; Aghdasi, M. PROMETHEE: A comprehensive literature review on methodologies and applications. *Eur. J. Oper. Res.* **2010**, *200*, 198–215. [\[CrossRef\]](#)
63. Keeney, R.L.; Raiffa, H.; Rajala, D.W. Decisions with Multiple Objectives: Preferences and Value Trade-Offs. *IEEE Trans. Syst. Man Cybern.* **1979**, *9*, 403. [\[CrossRef\]](#)
64. Edwards, W. How to Use Multiattribute Utility Measurement for Social Decision Making. *IEEE Trans. Syst. Man Cybern.* **1977**, *7*, 326–340. [\[CrossRef\]](#)
65. Pelissari, R.; Oliveira, M.C.; Abackerli, A.J.; Ben-Amor, S.; Assumpção, M.R.P. Techniques to model uncertain input data of multi-criteria decision-making problems: A literature review. *Int. Trans. Oper. Res.* **2018**, *28*, 523–559. [\[CrossRef\]](#)
66. Kahraman, C.; Uçal Sarı, İ. Multicriteria Environmental Risk Evaluation Using Type II Fuzzy Sets. In *International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems*; Springer: Berlin/Heidelberg, Germany, 2012; pp. 449–457. [\[CrossRef\]](#)
67. Kaya, İ.; Çolak, M.; Terzi, F. A comprehensive review of fuzzy multi criteria decision making methodologies for energy policy making. *Energy Strategy Rev.* **2019**, *24*, 207–228. [\[CrossRef\]](#)
68. Zadeh, L.A. Fuzzy sets. *Inf. Control* **1965**, *8*, 338–353. [\[CrossRef\]](#)
69. Dempster, A.P. Upper and Lower Probabilities Induced by a Multivalued Mapping. *Ann. Math. Stat.* **1967**, *38*, 325–339. [\[CrossRef\]](#)
70. Shafer, G. *A Mathematical Theory of Evidence*; Walter de Gruyter GmbH: Berlin, Germany, 1976. [\[CrossRef\]](#)
71. Mudashiru, R.B.; Sabtu, N.; Abustan, I.; Balogun, W. Flood hazard mapping methods: A review. *J. Hydrol.* **2021**, *603*, 126846. [\[CrossRef\]](#)
72. Liao, H.; He, Y.; Wu, X.; Wu, Z.; Bausys, R. Reimagining Multi-Criterion Decision Making by Data-Driven Methods Based on Machine Learning: A Literature Review. *Inf. Fusion* **2023**, *100*, 101970. [\[CrossRef\]](#)
73. Breiman, L. Random Forests. *Mach. Learn.* **2001**, *45*, 5–32. [\[CrossRef\]](#)
74. Cortes, C.; Vapnik, V. Support-Vector Networks. *Mach. Learn.* **1995**, *20*, 273–297. [\[CrossRef\]](#)
75. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* **2015**, *521*, 436–444. [\[CrossRef\]](#) [\[PubMed\]](#)
76. Ali, R.; Hussain, A.; Nazir, S.; Khan, S.; Khan, H.U. Intelligent Decision Support Systems—An Analysis of Machine Learning and Multicriteria Decision-Making Methods. *Appl. Sci.* **2023**, *13*, 12426. [\[CrossRef\]](#)
77. Linstone, H.A.; Turoff, M. (Eds.) *The Delphi Method: Techniques and Applications*, 1st ed.; Addison-Wesley Educational Publishers Inc.: Boston, MA, USA, 1975.
78. Shannon, C.E. A Mathematical Theory of Communication. *Bell Syst. Tech. J.* **1948**, *27*, 623–656. [\[CrossRef\]](#)
79. Jolliffe, I.T. *Principal Component Analysis*; Springer Series in Statistics; Springer: New York, NY, USA, 1986. [\[CrossRef\]](#)
80. Fontela, E.; Gabus, A. DEMATEL: Progress achieved. *Futures* **1974**, *6*, 361–363. [\[CrossRef\]](#)
81. Belton, V.; Stewart, T.J. The Multiple Criteria Problem. In *Multiple Criteria Decision Analysis*; Springer: Boston, MA, USA, 2002; pp. 13–33. [\[CrossRef\]](#)
82. Saltelli, A.; Ratto, M.; Andres, T.; Campolongo, F.; Cariboni, J.; Gatelli, D.; Saisana, M.; Tarantola, S. *Global Sensitivity Analysis: The Primer*; John Wiley & Sons: Hoboken, NJ, USA, 2007. [\[CrossRef\]](#)
83. Fishburn, P.C. Additive utilities with finite sets: Applications in the management sciences. *Nav. Res. Logist. Q.* **1967**, *14*, 1–13. [\[CrossRef\]](#)
84. Longley, P.A.; Frank Goodchild, M. Geographic Information Science and Systems. In *International Encyclopedia of Human Geography*; John Wiley & Sons: Hoboken, NJ, USA, 2020; pp. 29–36. [\[CrossRef\]](#)
85. Goodchild, M.F. The quality of big (geo)data. *Dialogues Hum. Geogr.* **2013**, *3*, 280–284. [\[CrossRef\]](#)

86. Hochrainer-Stigler, S.; Šakić Trogrlić, R.; Reiter, K.; Ward, P.J.; de Ruiter, M.C.; Duncan, M.J.; Torresan, S.; Ciurean, R.; Mysiak, J.; Stuparu, D.; et al. Toward a framework for systemic multi-hazard and multi-risk assessment and management. *iScience* **2023**, *26*, 106736. [[CrossRef](#)] [[PubMed](#)]
87. Jo, E.; Mackay, R.; Murai, M.; Therivel, R. *Guidance and Toolkit for Impact Assessments in a World Heritage Context*; UNESCO Publishing: Paris, France, 2022. [[CrossRef](#)]
88. Hajihassanpour, M.; Kesserwani, G.; Pettersson, P.; Bellos, V. Sampling-Based Methods for Uncertainty Propagation in Flood Modeling Under Multiple Uncertain Inputs: Finding out the Most Efficient Choice. *Water Resour. Res.* **2023**, *59*, e2022WR034011. [[CrossRef](#)]
89. Tomar, A.; Burton, H.V.; Mosleh, A. Dynamic updating of post-earthquake damage and functional restoration forecasts of water distribution systems using Bayesian inferencing. *Earthq. Spectra* **2022**, *38*, 109–127. [[CrossRef](#)]
90. Van Westen, C.J. Remote Sensing and GIS for Natural Hazards Assessment and Disaster Risk Management. *Treatise Geomorphol.* **2013**, *3*, 259–298. [[CrossRef](#)]
91. Stewart, T.J.; French, S.; Rios, J. Integrating multicriteria decision analysis and scenario planning—Review and extension. *Omega* **2013**, *41*, 679–688. [[CrossRef](#)]
92. Arrighi, C.; Masi, M.; De Lucia, C.; Castelli, F. Prioritizing risk for cultural heritage through social value: A participatory framework. *Int. J. Disaster Risk Reduct.* **2025**, *126*, 105627. [[CrossRef](#)]
93. Bhunia, G.S.; Shit, P.K. Geospatial Technology for Multi-hazard Risk Assessment. In *Geospatial Technology for Environmental Hazards*; Springer: Cham, Switzerland, 2021; pp. 1–18. [[CrossRef](#)]
94. Ward, P.J.; Daniell, J.; Duncan, M.; Dunne, A.; Hananel, C.; Hochrainer-Stigler, S.; Tijssen, A.; Torresan, S.; Ciurean, R.; Gill, J.C.; et al. Invited perspectives: A research agenda towards disaster risk management pathways in multi-(hazard-)risk assessment. *Nat. Hazards Earth Syst. Sci.* **2022**, *22*, 1487–1497. [[CrossRef](#)]
95. Bakhtiari, S.; Najafi, M.R.; Goda, K.; Peerhossaini, H. Toward Temporal Multi-Hazard Risk Assessment Using Dynamic Bayesian Network Analysis. In *Proceedings of the Canadian Society for Civil Engineering Annual Conference 2024*; Springer Nature: Cham, Switzerland, 2025; Volume 3, pp. 191–202. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.