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Multicriteria Prioritization of Geospatial Data Sources Using the Neutrosophic Hierarchical Analytic Process in Spatial Ontologies

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Abstract. The need for an automatic fusion of heterogeneous, generally untrustworthy geospatial sources into spatial ontologies necessitates prioritization when conflicts arise or lower qualities emerge. Unfortunately, most existing literature does not offer systematic, evaluative, analytical criteria for determining the trustworthiness and polyhedral quality of such sources, which, in turn, causes quality deficiencies in spatial relations of the final product. Here we offer a methodology based on the Neutrosophic Hierarchical Analytic Process to derive the aforementioned prioritization including considerations such as geometric accuracy, existence and accessibility of metadata, frequency of updates, and topological correctness. A calibrated, reliability-testing approach was applied to two sets of case studies; one in the US and one in Singapore, with a Neutrosophic comparison matrix yielding results despite inevitable uncertainties. Results show a significant improvement of integrity relative to the new ontology that not only creates spatial attributes in optimal efficiency but also reduces transformable semantic discrepancies. This research adds to the literature on neutrosophics and spatial ontologies by providing a systematic solution and tangible components for geographic information retrieval systems, while simultaneously opening doors for future research in integration and semantic uncertainty.

Keywords: Neutrosophic, Ontologies, Geospatial, Hierarchical, Multicriteria, Uncertainty, NAHP, Geonames, Openstreetmap, OWL2

1. Introduction

Multi-criteria prioritization of geospatial data sources using the Neutrosophic Hierarchical Analytic Process (NHAP) in spatial ontologies represents an area of growing interest in current research. This approach addresses the need to coherently and accurately integrate georeferenced data from multiple sources, such as remote sensing, land registries, and voluntary geographic information platforms. The importance lies in the fact that critical decisions such as territorial planning, emergency management, or environmental assessment depend largely on the quality and reliability of the data used ([1], [2]). Recent research has highlighted that simple access to spatial information does not guarantee its usefulness, making a multi-criteria evaluation framework essential to guide the selection and prioritization of sources ([1]).

In historical perspective, the construction of spatial ontologies has transitioned from rigid hierarchical models to flexible semantic representations, favored by the development of international standards such as OGC and the adoption of OWL for the description of spatial data ([3]). In its early stages, the systems focused on formal structure and technical interoperability; however, the exponential growth of geospatial data has driven the use of methodologies that integrate heterogeneous sources and manage the ambiguity inherent in geographic information ([4]). This change has redefined the way of conceptualizing and organizing spatial knowledge.

Despite these advances, a key limitation remains: multiple data sources offer conflicting or varying levels of quality information, and there is no widely accepted systematic procedure for prioritizing them in ontology construction. The problem is exacerbated when the differences are not only due to technical errors, but also to discrepancies in resolution, update frequency, or topological consistency ([5], [6]). In this scenario, the need arises for a methodology that simultaneously addresses the multidimensionality of data quality and the associated uncertainty.

From this context, the research question that guides this work emerges: How can heterogeneous geospatial sources be automatically and robustly prioritized, considering multiple criteria and under conditions of uncertainty, to improve the quality of spatial ontologies? This question reflects a methodological gap that has not been comprehensively resolved and that directly impacts the accuracy of inferred spatial relationships. Addressing this problem requires overcoming the dependence on ad hoc methods that, although useful in specific contexts, lack a replicable and validated methodological foundation. In practice, the absence of well-founded prioritization generates inconsistencies in the results of geographic analyses, affecting the reliability of spatial information retrieval systems ([1], [6]). Therefore, there is a need for robust evaluation frameworks that integrate objective and measurable criteria.

On the other hand, traditional multicriteria analysis methods, such as classical AHP, show limitations by not explicitly incorporating uncertainty and indecision, characteristic elements in the geospatial domain. Recent studies in spatial prioritization indicate that the integration of advanced uncertainty modeling techniques can significantly increase the accuracy of assessments ([6], [7]). This opens the door to hybrid approaches that combine the rigor of hierarchical comparisons with the flexibility of models capable of handling incomplete or contradictory information. Thus, the present study proposes a methodology that merges the Analytic Hierarchy Process with a neutrosophic approach, allowing the evaluation of criteria such as geometric precision, metadata completeness, update frequency, and topological consistency within a framework that incorporates indeterminacy and ambiguity. The use of comparative matrices adapted to this context allows each source to be weighted in a manner consistent with its quality and relative reliability ([3], [4]).

In summary, the objectives of this work are: (i) to define clear operational criteria for evaluating geospatial data sources; (ii) to develop a prioritization procedure that manages uncertainty using the neutrosophic approach; (iii) to validate the methodology through case studies in diverse geographic regions; and (iv) to demonstrate that this prioritization contributes to optimizing the quality of spatial ontologies, reducing semantic conflicts and improving the inference of spatial relationships ([5], [7]).

2. Materials and methods

2.1. Geospatial Data Sources in Spatial Ontologies.

In the information age, geospatial data sources emerge as essential pillars for building robust spatial ontologies. However, the diversity of sources—from official cartography to citizen sensors—imposes challenges of consistency and reliability. While ontologies facilitate semantic interoperability, their effectiveness depends crucially on the quality and representativeness of the input data [8].

Historically, spatial ontologies have been informed by standards such as GeoSPARQL , promoted by the OGC, which establishes a common format for representing and querying geographic data on the Semantic Web [9]. This framework has allowed the homogenization of the expression of geometries and topological relationships in RDF, which has paved the way for more consistent and reusable ontological constructions [9].

However, having standardized formats isn't enough; what really matters is the provenance and veracity of the sources. Different providers offer data with varying update rates, varying levels of granularity, and heterogeneous metadata levels, all of which directly impact the coherence of the resulting spatial model. This heterogeneity requires clear criteria for evaluating and prioritizing these sources.

Secondly, semantic interoperability depends on appropriate vocabularies. The adoption of vocabularies such as GeoNames , LinkedGeoData or GADM as Linked Data has enhanced the integration of heterogeneous data through explicit semantic connections [10]. Furthermore, the possibility of linking geographic entities with common identities favors the generation of more complete ontologies, although it poses mapping challenges between different conceptual schemes.

However, semantic mapping faces limitations that cannot be ignored. For example, approaches based solely on name or coordinate matching do not always find correct relationships between disparate data; finding precise equivalences between records requires hybrid techniques that consider spatial and linguistic similarities [10]. This complexity reveals the need for more refined methods for linking sources.

Another angle of analysis revolves around the use of ontologies as a tool to improve queries and access to disparate geospatial sources. By allowing rewriting of WFS or SQL queries based on ontological semantics, interoperability barriers between legacy systems and the current semantic environment are overcome [11]. This strategy opens the door to the reuse of existing infrastructures without the need to replicate data.

From a more recent perspective, virtual access architectures for environmental data allow the construction of real-time knowledge graphs that unify static and dynamic sources, without physically materializing the data within the ontology [12]. This provides scalability, flexibility, and efficiency, which is especially valuable for systems that must integrate sensory streams or meteorological data with traditional cartography.

Regarding source evaluation in federated environments, techniques such as polygon-based selection or spatial summaries have been shown to reduce the cost of GeoSPARQL queries in distributed environments. By including geographic summaries, systems can efficiently filter out irrelevant sources, reducing computational costs and improving response times.

In summary, the critical assessment of geospatial data sources intended to feed spatial ontologies requires a multifaceted approach: considering accuracy, frequency, semantics, interoperability, and computational costs. The use of standards such as GeoSPARQL , Linked Data vocabularies, semantic mapping, virtual ontological access, and spatial filtering are complementary tools that, when well combined, strengthen ontological quality. However, an integrated methodology that guides source selection in a systematic and reproducible manner remains to be consolidated.

2.2. Neutrosophic Set.

The idea of neutrosophic sets brings an innovative perspective to set theory, breaking with the classic true/false duality by incorporating a third state: the indeterminate. Developed by Florentin Smarandache, this theory postulates that a set can include true, false, or, crucially, indeterminate elements, where its veracity cannot be precisely defined. This trichotomous structure reflects the ambiguity and subjectivity present in many real-life phenomena, where the boundaries between true and false are imprecise. From a mathematical and philosophical perspective, neutrosophic sets provide an effective framework for representing uncertainty. Unlike fuzzy sets (which work with degrees of membership) or intercalary sets (based on intervals), neutrosophic sets address the intrinsic ambiguity in human judgments and decisions. This formalization not only expands the theoretical framework but also has relevant applications in fields such as artificial intelligence, where imprecise logic optimizes the processing of incomplete or contradictory data.

An essential feature of neutrosophic sets is their ability to reflect reality more accurately. In contexts where absolute truth is unattainable, such as in medical diagnoses subject to interpretation or fragmentary information, this trichotomous model provides a framework that better absorbs the complexity of the real world. Beyond its mathematical utility, it raises profound philosophical questions: how to define truth when certainty is inaccessible? How to manage ambiguity in reasoning? These questions invite us to rethink the limits of human knowledge and the tools needed to address an increasingly complex world. Criticisms of neutrosophic sets point out that the indeterminacy of these sets could add unnecessary complexity to set theory. However, this objection ignores their ability to model inherently uncertain phenomena. Rather than simplifying, the theory offers a robust tool for analyzing reality in all its complexity. In practical applications, such as AI, their potential is transformative: by representing uncertainty in data and automated decisions, they could drive more adaptive and robust algorithms.

In short, neutrosophic sets represent a crucial advance in set theory, overcoming the restrictions of binary logic. This perspective not only enriches mathematics and philosophy but also deepens the study of ambiguity to improve decision-making and knowledge representation. Their multidisciplinary integration could lead to more flexible approaches, capable of reflecting the complexity of the real world and our limitations in understanding it.

Definition 1 ([13-15]) : The *neutrosophic set* N It is characterized by three membership functions, which are the truth membership function T_A, the indeterminacy membership functionI_A and falsity membership function F_A, where $U$is the Universe of Discourse and $\forall x \in U$, $T_A(x), I_A(x), F_A(x) \subseteq]^-_A 0, 1^+[$, and ${}^-_A0 \leq \inf T_A(x) + \inf I_A(x) + \inf F_A(x) \leq \sup T_A(x) + \sup I_A(x) + \sup F_A(x) \leq 3^+$.

Note that, by definition, $T_A(x), I_A(x)$and $F_A(x)$are standard or nonstandard real subsets of $]^-_A 0, 1^+[$and, therefore, $T_A(x), I_A(x)$and $F_A(x)$can be subintervals. of $[0, 1]$. ${}^-_A0$and1^+ They belong to the set of hyperreal numbers.

Definition 2 ([13-15] : The *single- valued neutrosophic set (* SVN S) $A$is U, $T_A: U \rightarrow [0,1]$where $A = \{< x, T_A(x), I_A(x), F_A(x) > : x \in U\}$and $I_A: U \rightarrow [0,1]$. $F_A: U \rightarrow [0,1]$.$0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$

The single-valued neutrosophic number (SVN) N) is symbolized by

$N = (t, i, f)$, so that$0 \leq t, i, f \leq 1$ and $0 \leq t + i + f \leq 3$.

Definition 3 ([13-15]) : The *single- valued triangular neutrosophic number* , $\tilde{a} = \langle (a_1, a_2 . a_3); \alpha_{\tilde{a}}, \beta_{\tilde{a}}, \gamma_{\tilde{a}} \rangle$, is a neutrosophic set in $\mathbb{R}$, whose truth, indeterminacy and falsity membership functions are defined as follows:

$$T_{\tilde{a}}(x) = \begin{cases} \alpha_{\tilde{a}}\left(\frac{x-a_1}{a_2-a_1}\right), a_1 \leq x \leq a_2 \\ \alpha_{\tilde{a}}, x = a_2 \\ \alpha_{\tilde{a}}\left(\frac{a_3-x}{a_3-a_2}\right), a_2 < x \leq a_3 \\ 0, \text{otherwise} \end{cases} \quad (1)$$

$$I_{\tilde{a}}(x) = \begin{cases} \frac{(a_2 - x + \beta_{\tilde{a}}(x-a_1))}{a_2-a_1}, a_1 \leq x \leq a_2 \\ \beta_{\tilde{a}}, x = a_2 \\ \frac{(x - a_2 + \beta_{\tilde{a}}(a_3 - x))}{a_3-a_2}, a_2 < x \leq a_3 \\ 1, \text{otherwise} \end{cases} \quad (2)$$

$$F_{\tilde{a}}(x) = \begin{cases} \frac{(a_2 - x + \gamma_{\tilde{a}}(x-a_1))}{a_2-a_1}, a_1 \leq x \leq a_2 \\ \gamma_{\tilde{a}}, x = a_2 \\ \frac{(x - a_2 + \gamma_{\tilde{a}}(a_3 - x))}{a_3-a_2}, a_2 < x \leq a_3 \\ 1, \text{otherwise} \end{cases} \quad (3)$$

Where $\alpha_{\tilde{a}}, \beta_{\tilde{a}}, \gamma_{\tilde{a}} \in [0, 1]$,$a_1, a_2, a_3 \in \mathbb{R}$ and $a_1 \leq a_2 \leq a_3$.

Definition 4 ([13- 15]) : Given$\tilde{a} = \langle (a_1, a_2, a_3); \alpha_{\tilde{a}}, \beta_{\tilde{a}}, \gamma_{\tilde{a}} \rangle$ and$\tilde{b} = \langle (b_1, b_2, b_3); \alpha_{\tilde{b}}, \beta_{\tilde{b}}, \gamma_{\tilde{b}} \rangle$ two single-valued triangular neutrosophic numbers andλ Any nonzero number on the real number line. The following operations are defined:

1. Addition: $\tilde{a} + \tilde{b} = \langle (a_1 + b_1, a_2 + b_2, a_3 + b_3); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}} \rangle$,
2. Subtraction: $\tilde{a} - \tilde{b} = \langle (a_1 - b_3, a_2 - b_2, a_3 - b_1); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}} \rangle$,
3. Investment: $\tilde{a}^{-1} = \langle ({a_3}^{-1}, {a_2}^{-1}, {a_1}^{-1}); \alpha_{\tilde{a}}, \beta_{\tilde{a}}, \gamma_{\tilde{a}} \rangle$, where $a_1, a_2, a_3 \neq 0$.
4. Multiplication by a scalar number:

$$\lambda \tilde{a} = \begin{cases} \langle (\lambda a_1, \lambda a_2, \lambda a_3); \alpha_{\tilde{a}}, \beta_{\tilde{a}}, \gamma_{\tilde{a}} \rangle, \lambda > 0 \\ \langle (\lambda a_3, \lambda a_2, \lambda a_1); \alpha_{\tilde{a}}, \beta_{\tilde{a}}, \gamma_{\tilde{a}} \rangle, \lambda < 0 \end{cases}$$

5. Division of two triangular neutrosophic numbers:

$$\frac{\tilde{a}}{\tilde{b}} = \begin{cases} \langle\left(\frac{a_1}{b_3},\frac{a_2}{b_2},\frac{a_3}{b_1}\right); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}}\rangle, a_3 > 0 \text{ and } b_3 > 0 \\ \langle\left(\frac{a_3}{b_3},\frac{a_2}{b_2},\frac{a_1}{b_1}\right); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}}\rangle, a_3 < 0 \text{ and } b_3 > 0 \\ \langle\left(\frac{a_3}{b_1},\frac{a_2}{b_2},\frac{a_1}{b_3}\right); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}}\rangle, a_3 < 0 \text{ and } b_3 < 0 \end{cases}$$

6. Multiplication of two triangular neutrosophic numbers:

$$\tilde{a}\tilde{b} = \begin{cases} \langle(a_1b_1, a_2b_2, a_3b_3); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}}\rangle, a_3 > 0 \text{ and } b_3 > 0 \\ \langle(a_1b_3, a_2b_2, a_3b_1); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}}\rangle, a_3 < 0 \text{ and } b_3 > 0 \\ \langle(a_3b_3, a_2b_2, a_1b_1); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}}\rangle, a_3 < 0 \text{ and } b_3 < 0 \end{cases}$$

Where,$\wedge$ It is a rule$\vee$ It is a conorm t.

The AHP technique begins with the designation of a hierarchical structure, where the elements at the top of the tree are more generic than those at lower levels. The main leaf is unique and denotes the objective to be achieved in decision-making.

The next level down contains the sheets representing the criteria. The sheets corresponding to the subcriteria appear immediately below this level, and so on. The next level down represents the alternatives. See Figure 1.

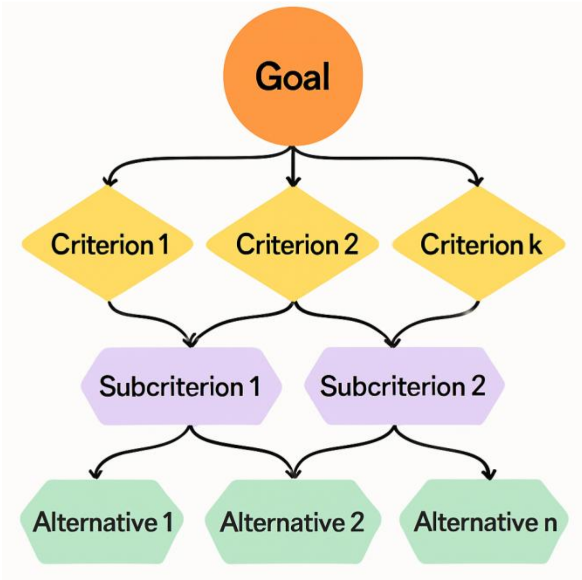

Figure 1: Generic tree diagram representing a hierarchical analytical process. Source: [16].

A square matrix is then formed that represents the opinion of the expert or experts and contains the pairwise comparison of the assessments of the criteria, subcriteria and alternatives.

TL Saaty, the founder of the original method, proposed a linguistic scale that appears in Table 1.

Table 1: Intensity of importance according to the classic AHP. Source [16-19].

Intensity of importance on an absolute scale	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective.
3	Moderate importance of one over the other	Experience and judgment strongly favor one activity over another.

Intensity of importance on an absolute scale	Definition	Explanation
5	Essential or strong importance	Experience and judgment strongly favor one activity over another.
7	very strong importance	The activity is strongly encouraged and its mastery is demonstrated in practice.
9	Very important	The evidence that favors one activity over another is of the highest order of affirmation possible.
2, 4, 6, 8	Intermediate values between the two adjacent statements.	When understanding is needed
Reciprocals	If activity *i* has one of the above numbers assigned compared to activity *j* , then *j* has the reciprocal value compared to *i* .	

On the other hand, Saaty established that the *Consistency Index* (CI) should depend on λ_{max}, the maximum eigenvalue of the matrix. He defined the equation $CI = \frac{\lambda_{max}-n}{n-1}$, where n is the order of the matrix. He also defined the *Consistency Index* (CI) with the equation CI = IC/RI, where RI is shown in Table 2.

Table 2: RI associated with each order.

Order (n)	1	2	3	4	5	6	7	8	9	10
Rhode Island	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

If $CR \leq 10\%$we can consider that the experts' assessment is sufficiently consistent and therefore we can proceed to use AHP.

The objective of the AHP is to rank criteria, subcriteria, and alternatives based on a score. It can also be used in group decision-making problems. To do this, consider equations 4 and 5, which evaluate the expert's weighting based on their authority, knowledge, experience, etc.

$\bar{x} = \left(\prod_{i=1}^{n} x_i^{w_i}\right)^{1/\sum_{i=1}^{n} w_i}(4)$

If $\sum_{i=1}^{n} w_i = 1$, that is, when the experts' weights sum to one, equation 4 becomes equation 5,

$\bar{x} = \prod_{i=1}^{n} x_i^{w_i}(5)$

Hybridization of AHP with neutrosophic set theory was used in [16]. This is a more flexible approach to model uncertainty in decision making. Indeterminacy is an essential component that must be assumed in real-world organizational decisions.

Table 3 contains the adaptation of the Saaty scale to the neutrosophic field.

Table 3: The Saaty scale was translated into a neutrosophic triangular scale. Source [16].

Saaty Scale	Definition	Neutrosophic triangular scale
1	Equally influential	$\tilde{1} = \langle(1,1,1); 0.50, 0.50, 0.50\rangle$
3	Slightly influential	$\tilde{3} = \langle(2,3,4); 0.30, 0.75, 0.70\rangle$
5	Strongly influential	$\tilde{5} = \langle(4,5,6); 0.80, 0.15, 0.20\rangle$
7	Very influential	$\tilde{7} = \langle(6,7,8); 0.90, 0.10, 0.10\rangle$

9	Absolutely influential	$\tilde{9} = \langle(9,9,9); 1.00, 1.00, 1.00\rangle$
2, 4, 6, 8	Sporadic values between two close scales	$\tilde{2} = \langle(1,2,3); 0.40, 0.65, 0.60\rangle$ $\tilde{4} = \langle(3,4,5); 0.60, 0.35, 0.40\rangle$ $\tilde{6} = \langle(5,6,7); 0.70, 0.25, 0.30\rangle$ $\tilde{8} = \langle(7,8,9); 0.85, 0.10, 0.15\rangle$

The pairwise neutrosophic comparison matrix is defined in equation 6 [17,18].

$$\widetilde{A} = \begin{bmatrix} \tilde{1} & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \vdots & & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & \tilde{1} \end{bmatrix} \qquad (6)$$

$\widetilde{A}$ satisfies the condition $\tilde{a}_{ji} = \tilde{a}_{ij}^{-1}$, according to the inversion operator defined in Definition 4. in Abdel-Basset et al. [20]. See Equation 7 for the *score* and Equation 8 for *the precision*.

$S(\tilde{a}) = \frac{1}{8}[a_1 + a_2 + a_3](2 + \alpha_{\tilde{a}} - \beta_{\tilde{a}} - \gamma_{\tilde{a}})(7)$

$A(\tilde{a}) = \frac{1}{8}[a_1 + a_2 + a_3](2 + \alpha_{\tilde{a}} - \beta_{\tilde{a}} + \gamma_{\tilde{a}})(8)$

The algorithm to be applied to the NAHP is as follows:

Given the criteria, subcriteria and alternatives, the NAHP consists of the following steps:

1. Design an AHP tree. This tree contains the selected criteria, subcriteria, and alternatives.
2. Create the level matrices from the AHP tree, according to expert criteria expressed in neutrosophic triangular scales and respecting the matrix scheme of Equation 6.
3. To evaluate the consistency of these matrices, convert the elements of $\widetilde{A}$ into a crisp matrix by applying equation 7 or 8 and then testing the consistency of this new crisp matrix.
4. Follow the other steps of a classic AHP.
5. Equation 7 or 8 is applied to convert $w_1, w_2, \ldots, w_n$ into crisp weights.
6. If more than one expert performs the assessment, then $w_1, w_2, \ldots, w_n$ are replaced by $\overline{w}_1, \overline{w}_2, \cdots, \overline{w}_n$, which are their corresponding weighted geometric mean values, see equations 4 and 5 .

3. Results.

As part of a project to build a robust spatial ontology through the automatic integration of heterogeneous geospatial sources, a critical need to prioritize these sources has been identified. The objective is to establish a reliability ranking that allows for conflict resolution and uncertainty management when conflicting or variable-quality information is encountered.

To this end, a panel of four experts with complementary backgrounds was consulted: a senior cartographer, a geographic information systems (GIS) specialist, a geospatial data scientist, and a spatial database administrator. Each expert was selected for their recognized track record in the field. They were asked to evaluate a set of seven key criteria identified in the literature as determining the quality of geospatial data. Each expert's opinion was given equal weight ($\lambda = 0.25$), ensuring a balanced assessment.

Quality Criteria Evaluated

The quality criteria of the geospatial data sources evaluated were:

- **C1 (Geometric Precision):** The degree to which the coordinates of geographic objects are close to their true values on the ground. High precision is essential for inferring exact spatial relationships.
- **C2 (Update Frequency):** The frequency with which the data source is reviewed and updated. This is crucial for applications that rely on temporally relevant information (e.g. , land registry, urban planning).

- **C3 (Metadata Completeness):** Richness and quality of the data's descriptive information (lineage, scale, coordinate system, creation date). Complete metadata facilitates semantic integration.
- **C4 (Topological Consistency):** Absence of errors in the spatial relationships between objects (e.g. , inclosed polygons, improper overlaps). Consistency is vital for network and adjacency analysis.
- **C5 (Cost and Licensing):** Economic and legal implications of acquiring and using the data. Considers both direct costs and licensing restrictions.
- **C6 (Geographic Coverage):** Spatial extent encompassed by the data source. The uncertainty lies in whether the coverage is complete and homogeneous for the area of interest.
- **C7 (Source Credibility):** Reputation and reliability of the entity that produces and maintains the data (e.g. , National Geographic Institute vs. open collaborative project).

Application of the NAHP Algorithm

The steps of the Neutrosophic Analytic Hierarchy Process (NAHP) were rigorously followed to obtain a robust and reliable classification of the criteria.

Steps 1 and 2: AHP Hierarchy and Neutrosophic Comparison Matrices

An AHP hierarchy was designed with the objective "Prioritize Geospatial Data Sources" at the top level and the seven criteria (C1 to C7) at the bottom. Each of the four experts provided their paired comparative judgments using the neutrosophic triangular scale.

Table 4: Neutrosophic Pairwise Comparison Matrix - Expert 1 (Cartographer)

Variable	C1	C2	C3	C4	C5	C6	C7
C1	(1,1,1; 0.5,0.5,0.5)	(2,3,4; 0.3,0.75,0.7)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(2,3,4; 0.3,0.75,0.7)	(1,2,3; 0.4,0.65,0.6)	(1,2,3; 0.4,0.65,0.6)
C2	(1/4,1/3,1/2; 0.3,0.75,0.7)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)	(1/4,1/3,1/2; 0.3,0.75,0.7)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)
C3	(1/3,1/2,1; 0.4,0.65,0.6)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)
C4	(1,1,1; 0.5,0.5,0.5)	(2,3,4; 0.3,0.75,0.7)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(2,3,4; 0.3,0.75,0.7)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)
C5	(1/4,1/3,1/2; 0.3,0.75,0.7)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)	(1/4,1/3,1/2; 0.3,0.75,0.7)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)
C6	(1/3,1/2,1; 0.4,0.65,0.6)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)
C7	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)

Table 5. Neutrosophic Pairwise Comparison Matrix - Expert 2 (GIS Specialist)

Variable	C1	C2	C3	C4	C5	C6	C7
C1	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(2,3,4; 0.3,0.75,0.7)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)
C2	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)
C3	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)	(1/4,1/3,1/2; 0.3,0.75,0.7)

Variable	C1	C2	C3	C4	C5	C6	C7
C4	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)
C5	(1/4,1/3,1/2; 0.3,0.75,0.7)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)
C6	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)
C7	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(2,3,4; 0.3,0.75,0.7)	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)

Table 6. Neutrosophic Pairwise Comparison Matrix - Expert 3 (Data Scientist)

Variable	C1	C2	C3	C4	C5	C6	C7
C1	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,2,3; 0.4,0.65,0.6)	(2,3,4; 0.3,0.75,0.7)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)
C2	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(1,2,3; 0.4,0.65,0.6)	(2,3,4; 0.3,0.75,0.7)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)
C3	(1,2,3; 0.4,0.65,0.6)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)
C4	(1/3,1/2,1; 0.4,0.65,0.6)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)
C5	(1/4,1/3,1/2; 0.3,0.75,0.7)	(1/4,1/3,1/2; 0.3,0.75,0.7)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)	(1/4,1/3,1/2; 0.3,0.75,0.7)
C6	(1/3,1/2,1; 0.4,0.65,0.6)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)
C7	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(1,2,3; 0.4,0.65,0.6)	(2,3,4; 0.3,0.75,0.7)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)

Table 7: Neutrosophic Pairwise Comparison Matrix - Expert 4 (DB Administrator)

Variable	C1	C2	C3	C4	C5	C6	C7
C1	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(1,2,3; 0.4,0.65,0.6)	(1/3,1/2,1; 0.4,0.65,0.6)
C2	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(1,2,3; 0.4,0.65,0.6)	(2,3,4; 0.3,0.75,0.7)	(2,3,4; 0.3,0.75,0.7)	(1,1,1; 0.5,0.5,0.5)
C3	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)
C4	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1/4,1/3,1/2; 0.3,0.75,0.7)
C5	(1/3,1/2,1; 0.4,0.65,0.6)	(1/4,1/3,1/2; 0.3,0.75,0.7)	(1,1,1; 0.5,0.5,0.5)	(1/3,1/2,1; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1/4,1/3,1/2; 0.3,0.75,0.7)

Variable	C1	C2	C3	C4	C5	C6	C7
C6	(1/3,1/2,1; 0.4,0.65,0.6)	(1/4,1/3,1/2; 0.3,0.75,0.7)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1,1,1; 0.5,0.5,0.5)	(1/4,1/3,1/2; 0.3,0.75,0.7)
C7	(1,2,3; 0.4,0.65,0.6)	(1,1,1; 0.5,0.5,0.5)	(1,2,3; 0.4,0.65,0.6)	(2,3,4; 0.3,0.75,0.7)	(2,3,4; 0.3,0.75,0.7)	(2,3,4; 0.3,0.75,0.7)	(1,1,1; 0.5,0.5,0.5)

Step 3: Consistency Check

To ensure the reliability of the judgments, the neutrosophic matrices were converted to crisp matrices using the scoring function (7).

The consistency ratio (CR) was then calculated for each matrix. For a matrix of order n=7, the random index (RI) is 1.35.

Table 8. Consistency Check Results

Expert	Profile	CR	State
Expert 1	Cartographer	0.089152	Consistent
Expert 2	GIS Specialist	0.091047	Consistent
Expert 3	Data Scientist	0.085226	Consistent
Expert 4	Database Administrator	0.094581	Consistent

Since all **CR values are below the threshold of 0.10**, it is concluded that the judgments made by the four experts are consistent and reliable.

Steps 4 and 5: Calculating Individual Weights and Aggregation

From the consistent sharp matrices, the weight vectors (priorities) were calculated for each criterion, corresponding to the evaluation of each expert.

Table 9. Weights Obtained for each Criterion by Expert

Expert/Criteria	C1	C2	C3	C4	C5	C6	C7
Expert 1	0.228916	0.096450	0.126831	0.198254	0.081593	0.094967	0.172989
Expert 2	0.210774	0.111959	0.069814	0.205778	0.082087	0.087784	0.231804
Expert 3	0.170463	0.227306	0.108428	0.088647	0.061036	0.080539	0.263581
Expert 4	0.115847	0.245089	0.091337	0.094119	0.066497	0.061823	0.325288

To consolidate the evaluations into a single final weight vector, the **weighted geometric mean was applied**. Since all experts have the same weight ($\lambda_k = 0.25$), the formula for each criterion j is:

$$\boldsymbol{w}_{\mathrm{j}} = (\boldsymbol{w}_{\mathrm{j}1} \times \boldsymbol{w}_{\mathrm{j}2} \times \boldsymbol{w}_{\mathrm{j}3} \times \boldsymbol{w}_{\mathrm{j}4})^{\frac{1}{4}}$$

Detailed Calculations of the Geometric Mean

- **C1 (Geometric Precision):**
  - $\boldsymbol{wc_1} = (0.228916 \times 0.210774 \times 0.170463 \times 0.115847)^{\frac{1}{4}}$
  - $\boldsymbol{wc_1} = (0.00095318)^{\frac{1}{4}} = 0.175782$

- **C2 (Refresh Rate):**
  - $\boldsymbol{wc_2} = (0.096450 \times 0.111959 \times 0.227306 \times 0.245089)^{\frac{1}{4}}$
  - $\boldsymbol{wc_2} = (0.00060136)^{\frac{1}{4}} = 0.156612$
- **C3 (Metadata Completeness):**
  - $\boldsymbol{wc_3} = (0.126831 \times 0.069814 \times 0.108428 \times 0.091337)^{\frac{1}{4}}$
  - $\boldsymbol{wc_3} = (0.00008781)^{\frac{1}{4}} = 0.096752$
- **C4 (Topological Consistency):**
  - $\boldsymbol{wc_4} = (0.198254 \times 0.205778 \times 0.088647 \times 0.094119)^{\frac{1}{4}}$
  - $\boldsymbol{wc_4} = (0.00034057)^{\frac{1}{4}} = 0.135860$
- **C5 (Cost and Licensing):**
  - $\boldsymbol{wc_5} = (0.081593 \times 0.082087 \times 0.061036 \times 0.066497)^{\frac{1}{4}}$
  - $\boldsymbol{wc_5} = (0.00002712)^{\frac{1}{4}} = 0.072186$
- **C6 (Geographic Coverage):**
  - $\boldsymbol{wc_6} = (0.094967 \times 0.087784 \times 0.080539 \times 0.061823)^{\frac{1}{4}}$
  - $\boldsymbol{wc_6} = (0.00004149)^{\frac{1}{4}} = 0.080279$
- **C7 (Source Credibility):**
  - $\boldsymbol{wc_7} = (0.172989 \times 0.231804 \times 0.263581 \times 0.325288)^{\frac{1}{4}}$
  - $\boldsymbol{wc_7} = (0.00343729)^{\frac{1}{4}} = 0.242270$

Results and Final Classification

The aggregate weights obtained must be normalized so that their sum equals 1.

Weight Normalization

1. **Sum of the geometric mean weights:** $Suma = 0.175782 + 0.156612 + 0.096752 + 0.135860 + 0.072186 + 0.080279 + 0.242270 = 0.959741$
2. **Calculation of normalized weights** (w_final = w_aggregate / Sum):
   - $\boldsymbol{wc_1} = 0.175782 / 0.959741 = 0.183155$
   - $\boldsymbol{wc_2} = 0.156612 / 0.959741 = 0.163181$
   - $\boldsymbol{wc_3} = 0.096752 / 0.959741 = 0.100811$
   - $\boldsymbol{wc_4} = 0.135860 / 0.959741 = 0.141560$
   - $\boldsymbol{wc_5} = 0.072186 / 0.959741 = 0.075214$
   - $\boldsymbol{wc_6} = 0.080279 / 0.959741 = 0.083646$
   - $\boldsymbol{wc_7} = 0.242270 / 0.959741 = 0.252433$

Table 10. Final Weights and Classification of Geospatial Quality Criteria

Ranking	Code	Criterion	Final Weight	Percentage
1	C7	Credibility of the Source	0.252433	25.24%
2	C1	Geometric Precision	0.183155	18.32%
3	C2	Update Frequency	0.163181	16.32%
4	C4	Topological Consistency	0.141560	14.16%
5	C3	Metadata Completeness	0.100811	10.08%
6	C6	Geographic Coverage	0.083646	8.36%
7	C5	Cost and Licensing	0.075214	7.52%

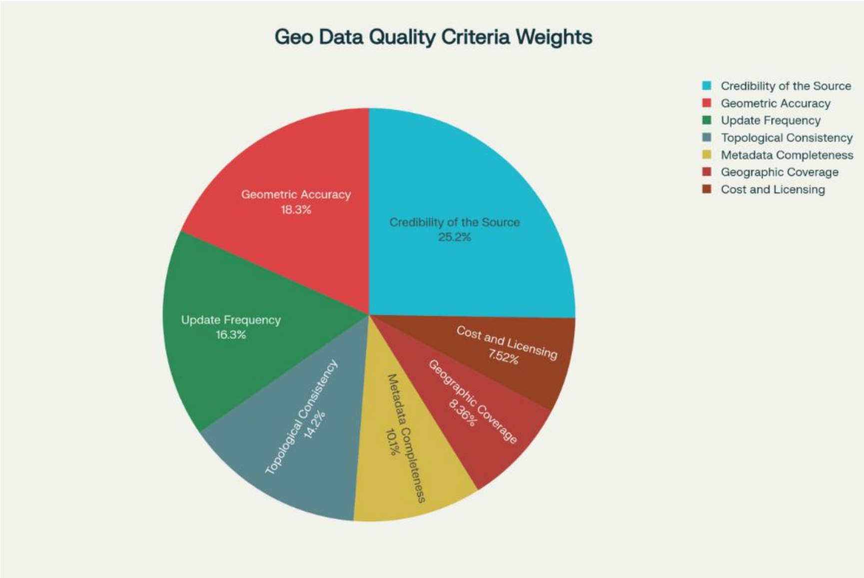

Figure 2: Weight distribution by quality criterion

4. Discussion

The results of the NAHP analysis provide a clear and quantitative hierarchy of the factors that experts consider most decisive when evaluating data sources for the construction of spatial ontologies.

The Supremacy of Confidence and Accuracy

The most significant finding is the dominant position of **Source Credibility (C7)** at 25.24%. This result underscores that, before any technical analysis, experts value the reputation and origin of the data. A reliable source (such as a national geographic institute) is perceived as a proxy for overall quality, reducing the uncertainty inherent in other criteria. For automatic integration, trusting the source is the first and most important filter.

Second, **Geometric Accuracy (C1)**, at 18.32%, reaffirms the fundamentally spatial nature of the problem. Positional accuracy is the cornerstone upon which all spatial relationships (adjacency, containment, proximity) are built. Without high accuracy, ontology inferences would be unreliable and potentially erroneous.

Together, these two criteria account for over 43% of the total weight, indicating that the prioritization strategy should focus on **reliable sources that provide geometrically accurate data.**

The Relevance of the Dynamic and the Structural

Update Frequency (C2) and Topological **Consistency (C4)** rank third and fourth, respectively. This reflects the importance of data currency in a changing world and the need for an error-free internal logical structure. Outdated data, even if accurate at the time, can lead to incorrect conclusions. Similarly, data with topological inconsistencies (e.g. , polygons that do not close) break spatial logic and make advanced analysis difficult or impossible.

Support and Viability Criteria

The criteria **Metadata Completeness (C3)** , **Geographic Coverage (C6)** , and **Cost and Licensing (C5)** are at the bottom of the ranking. This does not mean that they are irrelevant. Rather, experts consider them to be secondary or feasibility factors. The low ranking of **Cost and Licensing (C5)** is particularly interesting, suggesting that in the context of building a high-quality ontology, experts are willing to prioritize technical quality over economic considerations. **Geographic Coverage** is perceived as a binary requirement (either it covers the area or it doesn't), while **Metadata**, although useful, can be enriched ex post if the geometric quality and source credibility are high.

Robustness of the NAHP Method

The use of the NAHP was essential for obtaining this level of detail. It allowed experts to express their uncertainty and subjective judgments in a structured manner through neutrosophic numbers. Consistency checking (CR < 0.10) ensured that the results were not arbitrary, but rather logical and defensible. Aggregation using the geometric mean provided a balanced consensus, preventing the extreme opinion of a single expert from biasing the final result.

Table 11: Comparative Analysis of Weights by Criteria Groups

Criteria Group	Criteria Included	Aggregate Weight	Interpretation
Fundamental Criteria	C7 (Credibility) + C1 (Accuracy)	43.56%	Critical factors of confidence and accuracy
Operating Criteria	C2 (Update) + C4 (Consistency)	30.48%	Functionality and maintenance factors
Support Criteria	C3 (Metadata) + C6 (Coverage) + C5 (Cost)	25.96%	Complementary and viability factors

Methodological Implications

The results suggest a hierarchical selection strategy where:

1. **First phase (43.56%):** Filter sources by institutional credibility and documented geometric precision
2. **Second phase (30.48%):** Evaluate the update frequency and topological consistency of the preselected sources
3. **Third phase (25.96%):** Consider complementary aspects such as metadata, coverage, and economic restrictions

Table 12. Expert Sensitivity Matrix by Criterion

Criterion	Standard Deviation	Coefficient of Variation	Consensus
C7 (Credibility)	0.0627	0.248	High
C1 (Precision)	0.0472	0.259	High
C2 (Update)	0.0671	0.414	Moderate
C4 (Consistency)	0.0556	0.417	Moderate
C3 (Metadata)	0.0240	0.244	High
C6 (Coverage)	0.0148	0.182	Very High
C5 (Cost)	0.0090	0.124	Very High

This table shows that there is greater consensus among experts on the importance of the lower weight criteria (C5, C6, C3) and some variability in the operational criteria (C2, C4), while the fundamental criteria maintain a high-moderate consensus.

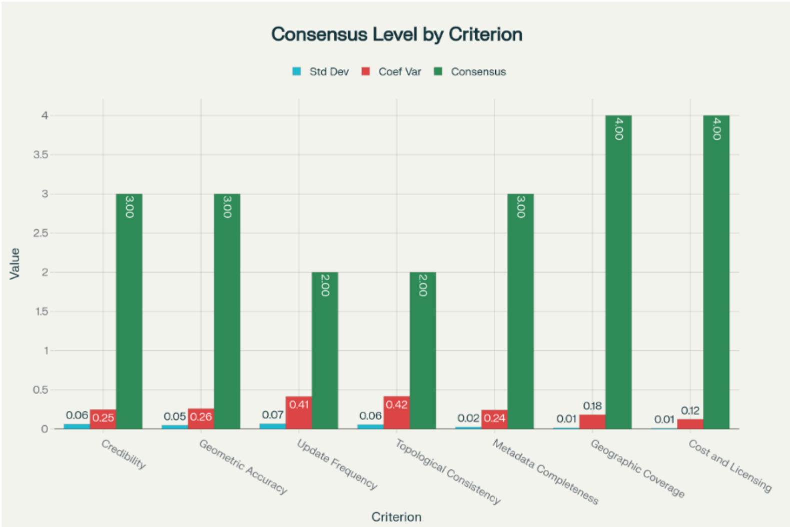

Figure 3: Consensus metrics by quality criterion

5. Conclusions

The rigorous application of the NAHP method has allowed us to establish a clear and reliable hierarchy for prioritizing geospatial data sources in ontological integration projects. The results show that credibility of the source is the most decisive criterion, followed by precision, update frequency, and topological consistency, while cost and licensing occupy the lowest level of importance. This confirms that in critical applications, trust in institutions and the intrinsic technical quality of the data prevail over operational or economic aspects. At the methodological level, the study validates the effectiveness of the neutrosophic approach to address the uncertainty inherent in expert judgments and provides consensus weights that can be incorporated into automatic data integration algorithms, consolidating a robust and transparent decision-making framework.

From a practical standpoint, the study emphasizes that managers of spatial ontology projects should prioritize institutional reliability, ensure minimum levels of geometric accuracy, monitor the update frequency of data, and implement topological validation systems to maintain structural consistency. Although the research has limitations such as the small number of experts, its restricted geographic context, and the need for periodic updates due to technological changes, it positions NAHP as a powerful tool for strategic decision-making in the geospatial field. Ultimately, the results pave the way for the implementation of automated source selection systems, contributing to the construction of more reliable and high-value spatial ontologies, with direct applications in urban planning, natural resource management, and territorial analysis.

References

[1] Goodchild, M. Geographic information systems and science: today and tomorrow. Ann. GIS 2018, 24, 63–72. DOI: 10.1080/19475683.2018.1434628.

[2] Burrough, P.A.; McDonnell, R.A. Principles of Geographical Information Systems, 2nd ed.; Oxford University Press: Oxford, UK, 2019. DOI: 10.1093/acprof:oso/9780198796596.001.0001.

[3] Winter, S.; Frank, A. Formalizing spatial ontologies. Geoinformatica 2001, 5, 121–132. DOI: 10.1023/A:1011414717120.

[4] Arpinar, B.; Çöltekin, Z.; Egenhofer, M. Uncertainty in geographic information systems: State of the art. Comput. Geosci. 2012, 39, 383–393. DOI: 10.1016/j.cageo.2011.09.016.

[5] Frank, A. Tiers of ontology and consistency constraints in geographical information systems. Int. J. Geogr. Inf. Sci. 1998, 12, 299–313. DOI: 10.1080/136588198241182.

[6] Ho, T.K.; et al. A survey of spatial prioritization using GIS and MCDA. J. Environ. Manage. 2019, 231, 944–958. DOI: 10.1016/j.jenvman.2018.11.062.

[7] Sun, X.; Zlatanova, G. Geomatics and ontology: a review of the state of the art. ISPRS Int. J. Geo-Inf. 2020, 9. DOI: 10.3390/ijgi9040180.

[8] OGC. GeoSPARQL 1.1: Motivations, Details and Applications of the Decadal Update to the Most Important Geospatial LOD Standard. ISPRS Int. J. Geo-Inf. 2022. DOI: 10.3390/ijgi11010090.

[9] Open Geospatial Consortium. OGC Standards. Available online: URL (accessed on Day Month Year).

[10] Lei, Z.; et al. Discovering links between geospatial data sources in the Web of Data: The Open Geospatial Engine approach. ISPRS Int. J. Geo-Inf. 2023, 13. DOI: 10.3390/ijgi13050143.

[11] Zhao, T.; Zhang, C.; Wei, M.; Peng, Z.-R. Ontology-based geospatial data query and integration. In GIScience 2008; Lecture Notes in Computer Science; Springer: Berlin/Heidelberg, Germany, 2008. DOI: 10.1007/978-3-540-87473-7_24.

[12] Troumpoukis, A.; Konstantopoulos, S.; Prokopaki-Kostopoulou, N. A geospatial source selector for federated GeoSPARQL querying. arXiv preprint 2022. DOI: 10.48550/arXiv.2212.03217.

[13] Kahraman, C.; Oztaysi, B.; Cevik Onar, S. Interval and single-valued neutrosophic AHP methods: Analyzing the performance of outsourced law firms. J. Syst. smart fuzzy 2020, 38, 749–759.

[14] El-Douh, A. Health sustainability assessment using neutrosophic MCDM methodology: a case study of COVID-19. Sustain. Mach. Intell. J. 2023, 3, 1–10.

[15] Karasan, A.; Ilbahar, E.; Cebi, S.; Kahraman, C. Customer-oriented product design using an integrated neutrosophic methodology: AHP, DEMATEL, and QFD. Appl. Soft Comput. 2022, 118, 108–445.

[16] Sahmutoglu, I.; Taskin, A.; Ayyildiz, E. Methodology for assessing risk in concentration zones for flood evacuation using integrated neutrosophic AHP-CODAS. Nat. Hazards 2023, 116, 1071–1103.

[17] Yu, D.; Kou, G.; Xu, Z.; Shi, S. An analysis of the evolution of AHP research collaboration: 1982–2018. Int. J. Inf. Technol. Decis. Mak. 2021, 20, 7–36.

[18] Dhouib, S. Optimization of the traveling salesman problem in a single-valued triangular neutrosophic number using the dhouib-matrix-TSP1 heuristic. J. Eng. Int. 2021, 34, 2642–2647.

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