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Qualitative spatial reasoning methodology to determine the particular domain of a set of geographic objects



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ABSTRACT

Nowadays, there are many geospatial information from different sources such as satellite images, aerial photographs, maps, databases and others. They provide a comprehensive description of geographic objects. However, the task to identify the geographic domain is not an easy task, because it involves a semantic processing related to inference approaches that are based on the conceptualization of a domain. These approaches allow us to understand in a similar way that human beings recognize the geographic entities and help us to avoid vagueness and uncertainty. In this paper, a methodology to perform a qualitative spatial reasoning in geospatial representations is proposed. It is based on *a priori* knowledge, which is explicitly formalized by means of an application ontology. The knowledge described in the ontology is assessed according to a set of labels, belonging to any geographical domain for semantic analysis and mapping those labels to matching concepts defined in the ontology. As result, a set of geographic domains ordered by their relevance is obtained, providing a general concept directly related to the input labels, simulating the way that we perceive cognitively any geographic domain in the real world.

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1. Introduction

Reasoning about spatial data is a key task in many applications, including geographic information systems (GIS), meteorological and fluid-flow analysis, computer-aided design, and protein structure databases (Guesgen, Ligozat, Renz, & Rodríguez, 2008). Such applications often require the identification and manipulation of qualitative spatial representations, for example, to detect whether one object will soon occlude another in a digital image or determine efficiently relationships between a proposed road and wetland regions in a geographic data set. Qualitative spatial reasoning (QSR) provides representational primitives (spatial “vocabulary”) and inference mechanisms for these tasks (Bailey-Kellogg & Zhao, 2003). QSR has two primary goals: providing a symbolic model for human common-sense level of reasoning and

providing efficient means for reasoning (Wolter & Lee, 2010).

The ability to perceive spatial objects and to reason about their relationships seems effortless for humans but it has proved that these actions are so difficult for computers. They have already attained the capabilities of a five-year-old child. Part of the computational problem lies in the difficulty of identifying and manipulating qualitative spatial representations. For example, although the pixels in a digital image define the locations of spatial objects implicitly, the task at hand might require a more qualitative characterization of the configuration of these objects, whether one object will soon occlude another (Bailey-Kellogg & Zhao, 1999).

Up-to-date GIS are becoming increasingly popular methods for representing and reasoning with geographical data (Elmes et al., 2005; Goodchild, 2009). These applications require methods of logical reasoning about geographical features and the relationships that hold between them, including spatially (Hobbs, Blythe, Chalupsky, & Russ, 2006; Lei, Kao, Lin, & Sun, 2009). The reasoning algorithms are widely used in the Artificial Intelligence field, whose the most relevant tasks are the capability of verifying the consistency of data sets, updating the shared knowledge, deriving new knowledge and finding a minimal representation

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(Donnelly, Bittner, & Rosse, 2006; Hernandez, 1994).

However, before performing any reasoning task, it is necessary to take into account a formal representation that allows us to conceptualize the domain knowledge of our interest (Renz, 2002; Buder & Schwind, 2012). In this case, ontologies are powerful tools to conceptualize any context, describing its concepts and expressing its relationships (Zhou, Ding, & Finin, 2011). Ontologies have also been cited as a method to carry out this reasoning (Mark, 2003; Egenhofer & Mark, 1995), but there are methodologies that do not handle the inherent vagueness adequately (Sharma, 1996). In fact, features are often dependent on the context in which they are made, with local knowledge affecting the definitions (Smith, 1996).

Geographic entities are not often a clearly demarcated entity, because they are part of another object (Liu & Daneshmend, 2004). Therefore, the individualization of entities is more important with respect to the geographic domains that they can belong or represent.

According to Bennett (2002), vagueness is inherent to the geographical domain, with many features being context dependent, as well as lacking precise definitions and boundaries. Vagueness is not a defect of our communication language but rather a useful and integral part. As a consequence, GIS cannot handle multiple possible interpretations in a correct manner, whereby the lack of this feature implies the creation of new techniques that allow the handling of various meanings, one of these is the inference based on reasoning.

Even though GISs are now a commonplace, the major problem is that of interaction. With gigabytes of information stored either in vector or raster format, present-day GISs do not sufficiently support intuitive or common-sense oriented human–computer interaction. Users may wish to abstract away from the mass of numerical data and specify a query in a way, which is essentially or at least largely, qualitative (Cohn & Renz, 2008). Arguably, the next generation GIS will be built on concepts arising from *Naïve Geography* (Egenhofer & Mark, 1995). Much of naïve geography should employ qualitative reasoning techniques, perhaps combined with the provision of “spatial query by sketch” (Egenhofer, 1997).

Qualitative reasoning is (QR) concerned not only with capturing the everyday common-sense knowledge of the physical world, but also the myriad equations used by engineers and scientists to explain complex physical phenomenon, while creating quantitative models (Weld & Kleer, 1989). The main goal of qualitative reasoning is to make this knowledge explicit, so that given appropriate reasoning techniques, a machine could make predictions, diagnostics and explanations of the behavior of physical systems in a qualitative manner, without recourse to an often intractable or perhaps unavailable quantitative model. According to that, note that although one use for qualitative reasoning is that it allows inferences to be made in absence of complete knowledge. It makes this not by probabilistic or fuzzy techniques, which may rely on arbitrarily assigned probabilities or membership values, but also by refusing to differentiate between quantities unless there is sufficient evidence to do so (Cohn & Hazarika, 2001).

The essence of QR is to find ways to represent continuous properties of the world by discrete systems of symbols. One can always quantize something continuously, but not all quantizations are equally useful. One-way to state the idea is the relevance principle: the distinctions made by a quantization must be relevant to the kind of reasoning performed (Forbus, 1984). The resulting set of qualitative values is termed a quantity space, in which indistinguishable values have been identified into an equivalence class. There is normally a natural ordering (either partial or total) associated with a quantity space, and one form of simple but effective inference is to exploit the transitivity of the ordering relationship.

Another is to devise qualitative arithmetic algebras (Wolter & Zakharyashev, 2000), typically these may produce ambiguous answers. Much research in the qualitative reasoning literature is devoted to overcoming the detrimental effects on the search space resulting from this ambiguity.

On the other hand, spatial reasoning in our everyday interaction with the physical world, in most cases is driven by qualitative abstractions rather than complete *a priori* quantitative knowledge. Therefore, QR holds promise for developing theories for reasoning about space. This justifies the increasing interest in the study of spatial concepts from a cognitive point of view, which provoked the birth of qualitative spatial reasoning within Artificial Intelligence and also GIS (Cohn, Bennett, Gooday, & Gotts, 1997).

Research in QSR is motivated by a wide variety of possible applications areas including GIS, robotic navigation, high level vision, spatial propositional semantics of natural languages, engineering design, common-sense reasoning about physical systems and specifying visual language syntax and semantics. There are other application areas including qualitative document-structure recognition (El-Geresy & Abdelmoty, 2006), applications in biology (Schlieder, 1996) and domains where space is used as a metaphor (Bennett, 1996; Knauff, Strube, Jola, Rauh, & Schlieder, 2004).

The goal of answering qualitative queries addresses an important aspect of common-sense reasoning by human beings and it can be found in many practical applications such as computer-aided tutoring or diagram understanding. Because of the lack of detailed numeric information, representations used by the approaches to data-poor problems are often carefully designed by hand with respect to an automatic task (Rauh et al., 2005).

In this work, we propose a methodology to perform a qualitative spatial reasoning, over a set of geospatial objects that are represented as input labels and belongs to a certain geographic domain. Three algorithms that perform the spatial reasoning and the inference tasks are proposed. They use the knowledge explicitly defined into application ontology and conceptual frameworks. The reasoning process is fundamentally based on the compute of topological relationships, which are used to describe the behavior of a geospatial object and their interaction with others.

The paper is organized as follows: Section 2 presents the state of the art related to the work in this field. Section 3 describes the proposed methodology to perform the qualitative spatial reasoning. Section 4 depicts the experimental results, applying the reasoning algorithms. The conclusion and future works are outlined in Section 5.

2. Related work

Spatial reasoning is an important issue in many application domains and it has been presented since the theory of points and lines geometry, which is considered one of the oldest branched of spatial reasoning (Renz, 2002). Other works on qualitative spatial reasoning are preceded by proposals oriented to spatial representations, in which the goal is that they can be read and understood by a machine (Sharma, 1996). In (Freksa, 1992) the importance of a correct representation of the reality to perform an efficient spatial reasoning process is described. In this case, machines are used to represent knowledge in a formal approach. However, the captured information must contain descriptions as close to how the human beings perceive their environment (Egenhofer & Mark, 1995). Thus, one of the main objectives of qualitative spatial reasoning is to find appropriate methods to represent continuous properties in the world, using a discrete symbols-based system (Cohn et al., 1997; Cohn & Hazarika, 2001).

According to the basis of QSR, in (Mark & Frank, 1991) some cognitive aspects of perception and knowledge representations as

well as the explanation why spatial knowledge is of a particular interest for cognitive science are explored. It is suggested that “spatial inference engines” provide the basis for rather general cognitive capabilities inside and outside the spatial domain. The role of abstraction in spatial reasoning and the advantages of qualitative spatial knowledge over quantitative knowledge are discussed. Thus, in (El-Geresy & Abdelmoty, 2004) a general qualitative spatial reasoning engine (SPARQS) is proposed. Qualitative treatment of information in large spatial databases is used to complement the quantitative approaches to manage those systems; in particular, it is used for the automatic derivation of implicit spatial relationships and in maintaining the integrity of the database. To be of practical use, composition tables of spatial relationships between different types of objects need to be developed and integrated in those systems. Examples of the application of the method using different objects and different types of spatial relationships are presented and new composition tables are built using the reasoning engine. Issues related to computer–human interaction (CHI) integrating qualitative spatial reasoning into GIS are proposed. In (Schultz, Guesgen, & Amor, 2006) three CHI challenges when combining qualitative and quantitative methods are addressed. (1) Manage the subjective, ambiguous nature of qualitative terms, (2) Provide a powerful, yet simple query system, and (3) effectively visualizing a complex, fuzzy qualitative query solution. A qualitative GIS called *TreeSap* is presented, which demonstrates that, with the use of CHI principles, query tools can be both powerful and accessible to non-expert users.

In (Randell, Cui, & Cohn, 1992), a study about the evolution of qualitative spatial representations is presented. Authors proposed a set of binary relations $C(x,y)$. For instance, according to the demonstration, the relationship “ x connects y ” is defined as symmetric and reflexive relationship. These kinds of relationships have been defined to work with spatial regions, where vagueness can be more common among geographic entities. Other proposals focused on incorporating qualitative spatial reasoning into GIS have been developed (Bennett, Cohn, & Isli, 1997). In this work, a logical approach based on formal logical representations and reasoning algorithms for manipulating qualitative spatial information is defined.

In (Wallgrün, 2010), the qualitative spatial reasoning methods

for learning the topological map of an unknown environment are described. The proposal consists of developing a topological mapping framework that achieves robustness against ambiguity in the available information by tracking all possible graph hypotheses simultaneously. They exploit spatial reasoning to reduce the space of possible hypotheses. The considered constraints are qualitative direction information and the assumption that the map is planar. The effects of absolute and relative direction information using two different spatial calculi and combine the approach with a real mapping system based on Voronoi graphs are investigated.

Spatial reasoning has been applied to topographical data with a grounded geographical ontology (Mallenby & Bennett, 2007). The method consists of handling the vagueness in the domain more effectively. It uses methods of reasoning about the spatial relations between regions within the data in order to use knowledge about regions defined in an ontology and allow reducing the computation of points location in the spatial relationships. In (Wang, Liu, Wang, & Liu, 2006), the conception and implementation of a tool based on spatial reasoning and spatial data mining (SRSDM) is presented. In this work a new spatial knowledge representation that integrates topology, direction, distance and size relations is proposed. SRSDM includes the following features: extracting spatial relations, frameworks for traditional or new data mining algorithms. As a case study, SRSDM has been tested with agricultural data.

On the other hand, the problem to understand the semantics based on spatial reasoning about oriented straight-line segments is presented in (Moratz, Lücke, & Mossakowski, 2011). According to the problem, it is difficult to establish a sound constraint calculus based on these relations. In this work, authors present the results of a new investigation into dipole constraint calculi, which uses algebraic methods to derive sound results about the composition of relations of dipole calculi. The method is denominated *condensed semantics*, and it is an abstract symbolic model of a specific fragment of our domain. It is based on the fact that qualitative dipole relations are invariant under orientation preserving affine transformations. The dipole calculi allows for a straightforward representation of prototypical reasoning tasks for spatial agents. In the same context, in (Wolter & Lee, 2010) an approach to qualitatively process directional relations, based on constraints that represents

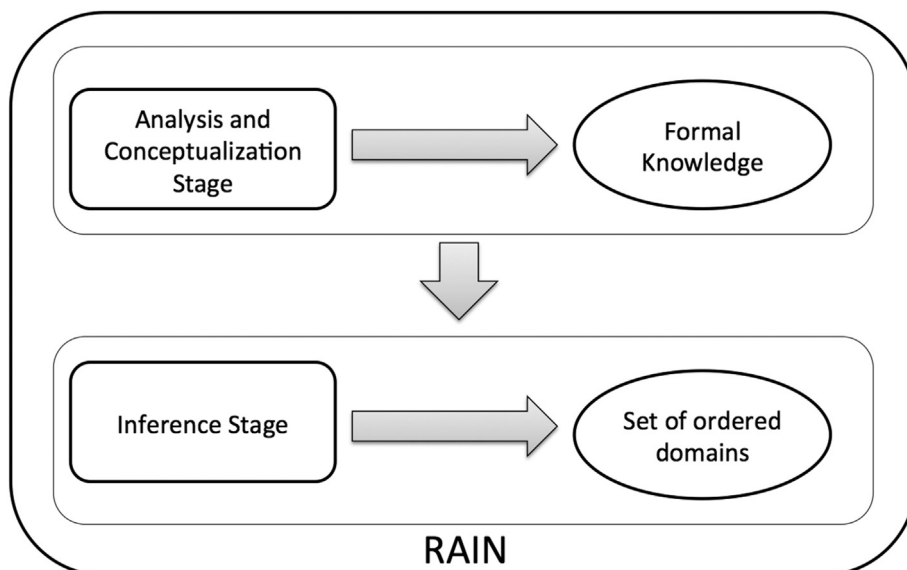


Fig. 1. General framework of the RAIN methodology.

positions in the plane is described.

Problems associated with the integration of data between incongruent boundary systems are outlined in (Eagleson, Escobar, & Williamson, 2003). The majority of spatial boundaries are designed in an uncoordinated manner with individual organizations, generating individual boundaries to meet individual needs. As a result, current technologies for analyzing geospatial information, such as GISs, are not reaching their full potential. In response to the problem of uncoordinated boundaries, the authors present an algorithm for the hierarchical structuring of administrative boundaries. This algorithm applies hierarchical spatial reasoning theory to the automated structuring of polygons. In turn, these structured boundary systems facilitate accurate data integration and analysis whilst meeting the spatial requirements of selected agencies. Moreover, the formalization and reasoning about spatial semantic integrity constraints is presented in (Bravo & Rodríguez, 2012). The paper presents a formalization of spatial semantic integrity constraints that provides a uniform specification of constraints used in practice, which is fundamental to assess the data quality of spatial databases. The formalization extends traditional notions of functional and inclusion dependencies to consider spatial attributes. This enables to impose topological relations between spatial attributes and constraints on numerical attributes that depend on spatial attributes. In (Grütter, Bauer-Messmer, & Hägeli, 2008), two approaches to represent the Region Connection Calculus (RCC) method in OWL-DL are described. The approaches are used to infer the relationships between all connecting spatial regions in any of the different RCC species using a complete calculus. The application is focused on searching spatial objects using an ontology.

In similar application context, the qualitative spatial reasoning has been used for high-resolution remote sensing image analysis (Brennan & Sowmya, 1998). In (Inglada & Michel, 2009), the Region Connection Calculus technique is used for the analysis of satellite imagery in order to fully exploit the richness of this kind of images. The processing consists of detecting complex objects and studying the relationships between the elementary objects that compose them. A graph-based representation of the spatial relationships between the regions of an image is used within a graph-matching procedure in order to implement an object detection algorithm.

In robotic navigation and computer vision fields, there are proposals for manipulation planning using qualitative spatial reasoning. In (Westphal, Dornhege, Wölfl, Gissler, & Nebel, 2011), an approach to generate heuristics for the probabilistic sampling strategy from spatial plans that abstract from concrete metric data is presented. These spatial plans describe a free trajectory in the workspace of the robot on a purely qualitative level, i.e., by employing spatial relations from formalisms considered in the domain of qualitative spatial and temporal reasoning. A discussion of such formalisms and constraint-based reasoning methods is outlined. These formalisms can be applied to approximate geometrically feasible motions.

3. RAIN methodology

RAIN is a methodology that consists of establishing a set of approaches to perform a qualitative spatial reasoning task in semantic descriptions of the geographic context, taking into account *a priori* knowledge of the geospatial domain. Thus, this knowledge is formalized by means of an application ontology, so that it can be readable by a machine.

RAIN is focused on the conceptualization of the concepts and relationships involved in a given domain. It is proposed to answer a question about which domain belongs to a set of semantic descriptions and what is the relevance of the concepts in that domain.

RAIN allows us to know the domain or context of a set of semantic descriptions that could appear disjointed. The methodology is composed of two stages: 1) *Analysis and conceptualization* and 2) *Inference*. In the first stage, we obtain the *a priori* knowledge, which is defined according to the reasoning requirements. In the second stage, a set of ordered domains, considering the proximity or similarity of the input descriptions is obtained. The general framework of the RAIN methodology is shown in Fig. 1.

3.1. The analysis and conceptualization stage

The conceptualization task is based on GEONTO-MET approach (Torres, Quintero, Moreno-Ibarra, Menchaca-Mendez, & Guzman, 2011), which is a methodology to build geographic domain ontologies. In Fig. 2, the conceptualization process is depicted.

By considering GEONTO-MET, two sets of axiomatic relations $A_1 = \{\text{is, has, does}\}$ and $A_2 = \{\text{prepositions}\}$ are used, in order to directly translate the relationships between concepts, as a part of the conceptualization. In other words, the aim is to reduce the axiomatic relationships in the ontology. For instance, topological relations such as connect, contain, meet and among others are defined as relational concepts in the conceptualization, whereupon more expressivity, granularity and semantic richness in the representation are obtained (Torres et al., 2011).

3.1.1. The abstraction process

This process is in charged of making an exhaustive revision over geographic objects that are involved in the set of geographic domains, in order to carry out an abstraction that defines *a priori* knowledge. Information of the domains has been gathered from *Kaab-Ontology*,¹ defined in (Torres et al., 2011). The advantage of this ontology domain is that we can find abstract entities and their relationships. In addition, definitions of the dictionary of National Institute of Statistics, Geography and Informatics of Mexico (INEGI) (INEGI, 1996) and National Center of Biomedical Ontologies (NCBO) are used. The result of the process is to obtain the essential information of geographic objects and domains that are of interest for the reasoning. In Fig. 3, a fragment of the proposed ontology, using *Kaab-Ontology* is depicted.

3.1.2. The synthesis process

This process receives the objects and domains from the abstraction task, which will be used in the reasoning stage. It is important to point out that information is not structured yet; therefore, it is necessary to define each domain according to its object interaction or relationship involved in the domain. Thus, a topological relation is defined between the geographic objects. A hierarchical relation described among them, considering their properties and synonyms in such domains as well as in geographic objects, represented in this relationship.

In this process a *mapping* of the geographic objects is carried out, with respect to the defined concepts in the application ontology. The mapping is performed for starting the population of the ontology with instances.

Kaab-Ontology contains a set of abstract entities of the geographic domain, which aids to delimitate the domain and restrict the number of concepts that are involved in each one. Fig. 4 shows the synthesis process, where we can appreciate that the set of concepts and topological relations allow the definition of domains set, in which the domains interact with the ontology to extract the instances that will generalize the process. In other words, from the description of many *specialized* concepts, a *general*

¹ *Kaab* means Earth in Mayan language.

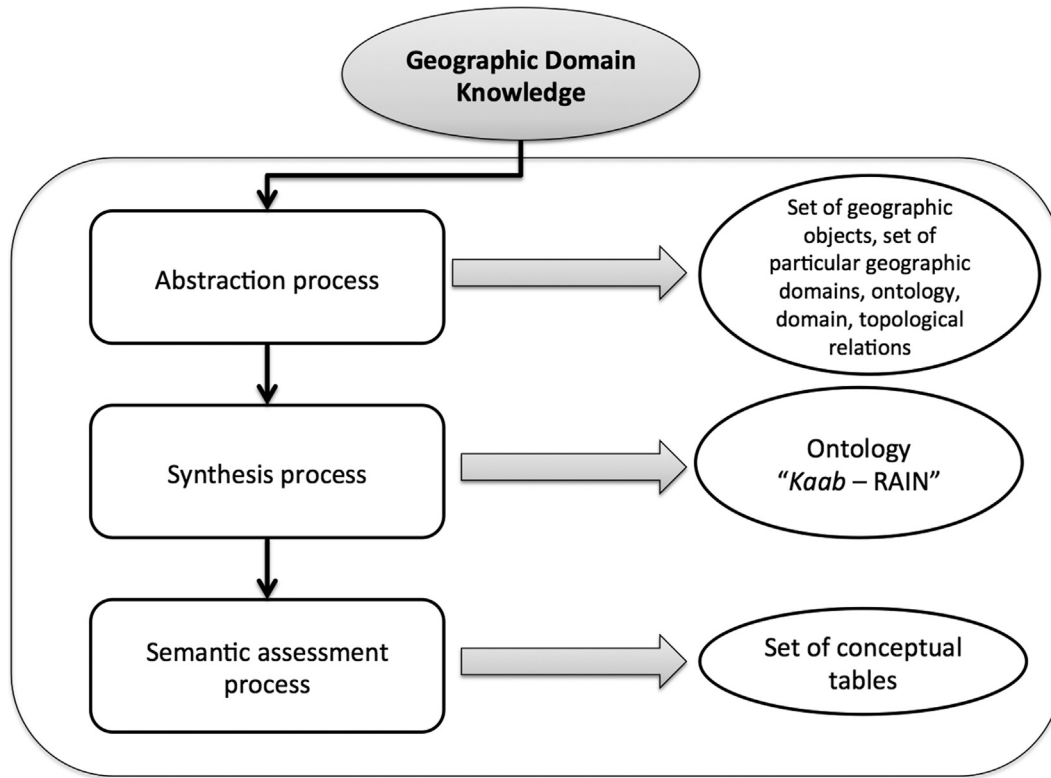


Fig. 2. Tasks of the conceptualization process.

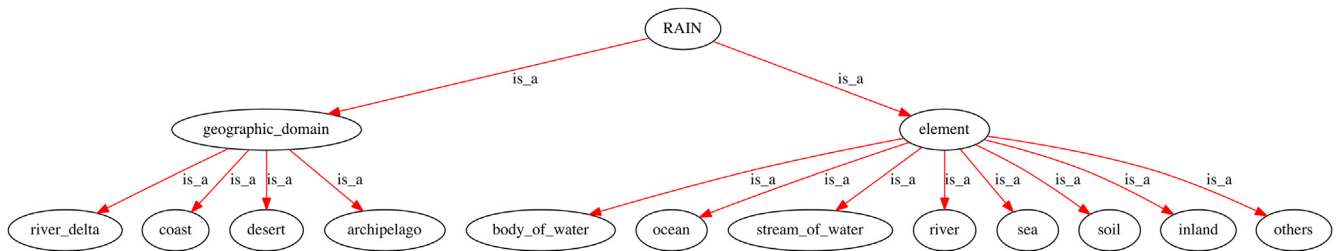


Fig. 3. Fragment of the RAIN ontology.

concept is obtained, which describes in a global form the concepts in a given domain.

Moreover, in Fig. 5 the mapping approach related to link instances with *Kaab* and *RAIN* ontologies is presented.

3.1.3. The semantic assessment process

The semantic assessment process uses the ontology and a set of tables for obtaining information with respect to concepts definition, their relationships with other concepts as well as their domains, rules and constraints. The goal of this task is to refine and assign a semantic value to each domain, taking into account the construction of concepts tables, which are composed of the properties, location in the hierarchy, names and synonyms, as well as a synonyms concepts table, a domains table, a synonyms domains table, a frequency table of concepts in the domains, a composition table of ordered topological relations according to their relevance, and finally a semantic refinement table in order to improve the inference method based on the feedback. These tables are defined as follows.

3.1.3.1. The concepts table. In this table, all the possible concepts that are part of each domain are shown. It allows us to explicitly express the characteristics that each concept contains. The table has information about the synonyms such as concepts and properties that are generally known. Additionally, the location of each concept in the hierarchy is known, identifying the concept nodes: father and child of each one. Every concept can have n number of children, but they only have one father. Thus, the relationships that can interact on that concept are expressed in the hierarchy too. Finally, application ontology with the properties, concepts that contain the domains and the hierarchy of each concept is generated (see Fig. 6).

On the other hand, let us describe the definitions for generating the concepts table (see Table 1) as follows.

For a concepts table, let c_{ij} be a concept that belongs to the set C , whereby a function $father(c_{ij})$ is proposed to return a concept $c_{p,q}$, which is defined as the father of c_{ij} .

Thus, let c_{ij} be a concept related to the function $child(c_{ij})$ that returns the concept(s) $c_{p,q}$, which is (are) child (children) of c_{ij} . Therefore, the function is defined as follows: $child(c_{ij})=c_{p,q}$.

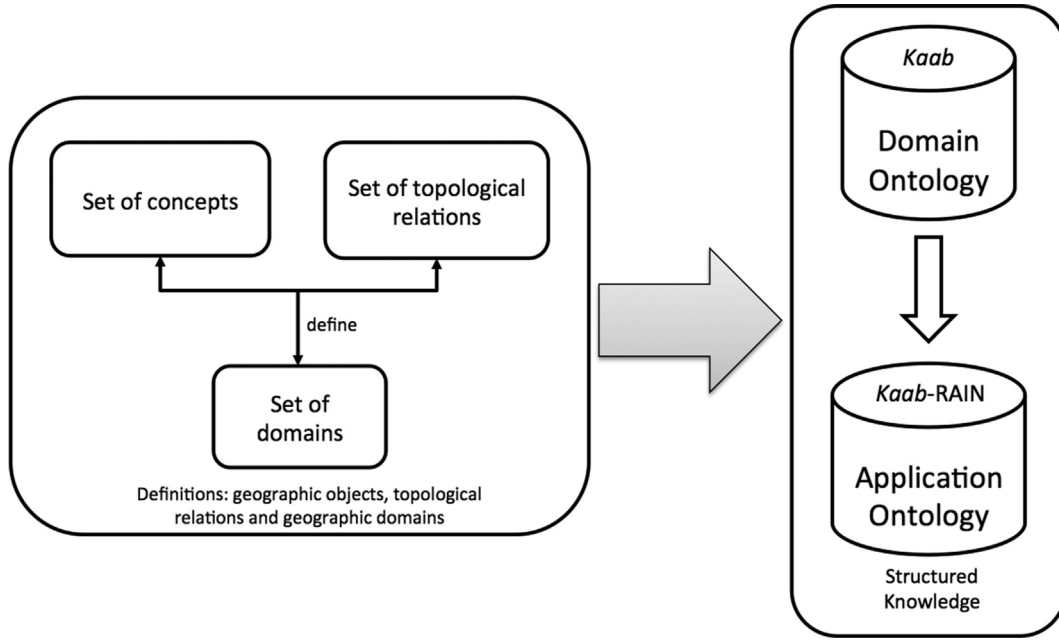


Fig. 4. Representation of the synthesis process.

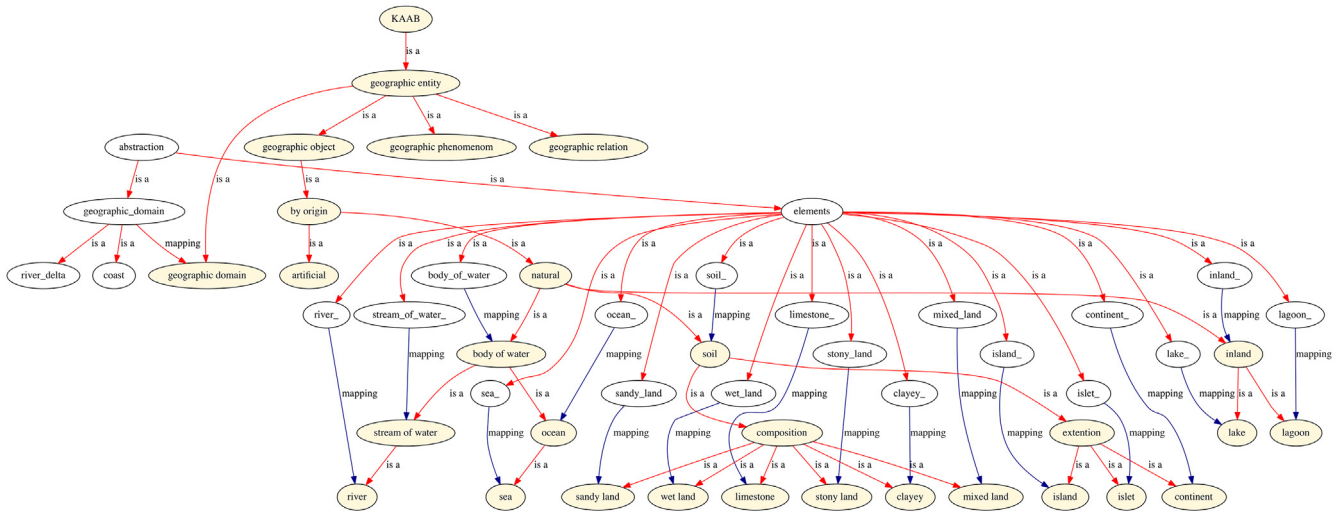


Fig. 5. The mapping approach.

Let P_{ij} be the set of properties that directly belongs to a concept c_{ij} , of a particular domain $d_i | d_i \in D$, which is defined by $P_{ij} = p(i,j,1), p(i,j,2), \dots, p(i,j,n)$.

According to the relationships, let R_{ij} be a set of topological relations that are associated to a concept c_{ij} of a particular domain $d_i | d_i \in D$, which is defined by $R_{ij} = r(i,j,1), r(i,j,2), \dots, r(i,j,n)$.

By taking into account those definitions, the function *exist-concept* receives a label et_i and returns the identification number of the interest concept. Otherwise, if the concept does not exist, a Boolean value is returned ("false" in this case). The function is defined as follows.

$$\text{exist_concept}(et_i) = \begin{cases} c_j & 0 \leq j \leq n \\ \text{false} & \text{dof} \end{cases}$$

In order to generate the concepts table, it is necessary to define

the function *exist_synonymous*, which receives a label and returns the number of the interest concepts or their relevancy. Otherwise, if the concept does not have any synonymous, the function returns a Boolean value ("false" in this case), when any concept has a synonymous. It is defined as follows.

$$\text{exist_synonymous}(et_i) = \begin{cases} c_j & 0 \leq j \leq n \\ \text{false} & \text{dof} \end{cases}$$

3.1.3.2. The frequency table of concepts in the domains. According to the collected information of each domain previously defined, there is a set of concepts that belongs to a particular domain. Thus, we can obtain the frequency of the concepts in the geographic domains.

Therefore, let D be the set of domains, where d is a particular

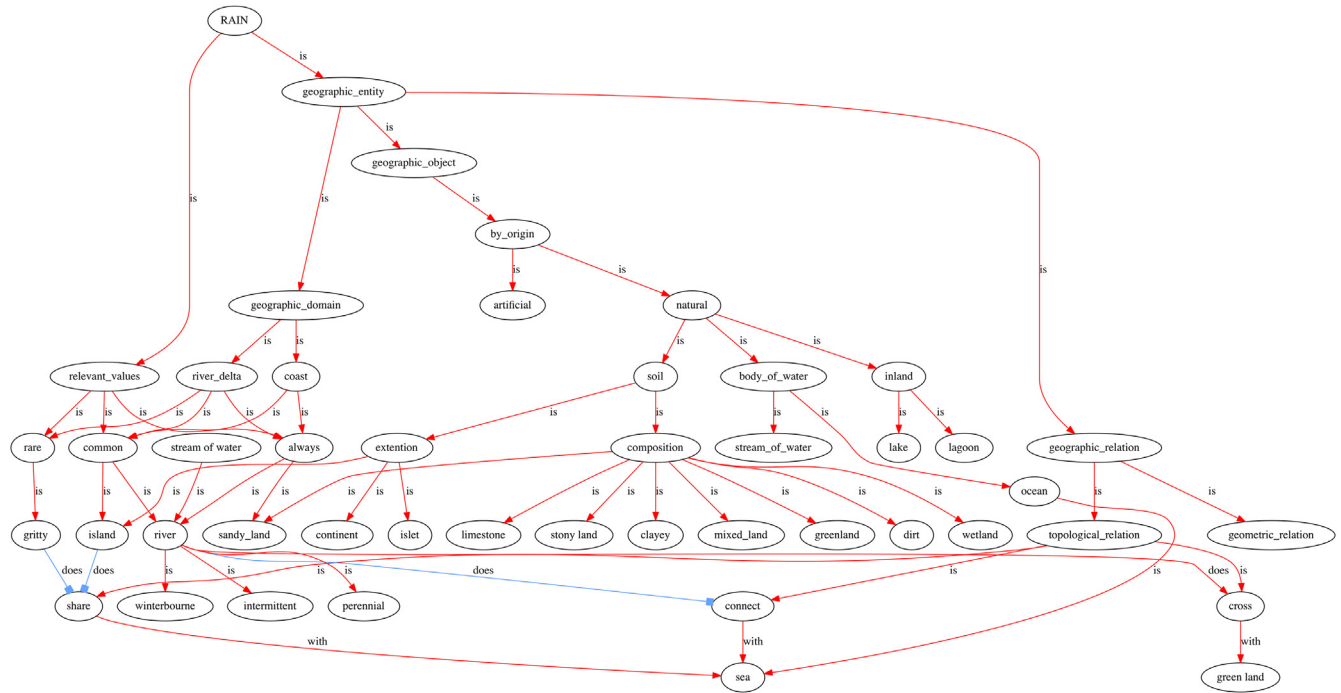


Fig. 6. RAIN ontology obtained from the semantic assessment process.

Table 1
The concepts table.

Concept name	Synonyms	Property	Father	Child	Topological relation
$c_{i,1}$	$S_{i,1}$	$P_{i,1}$	$father(c_{i,1})$	$child(c_{i,1})$	$R_{i,1}$
$c_{i,2}$	$S_{i,2}$	$P_{i,2}$	$father(c_{i,2})$	$child(c_{i,2})$	$R_{i,2}$
...
$c_{i,n}$	$S_{i,n}$	$P_{i,n}$	$father(c_{i,n})$	$child(c_{i,n})$	$R_{i,n}$
...
$c_{m,n}$	$S_{m,n}$	$P_{m,n}$	$father(c_{m,n})$	$child(c_{m,n})$	$R_{m,n}$

geographic domain that has been defined by the following expression: $D=d_1, d_2, \dots, d_n$. Now, let C be the set of domains, in which c is a concept involved in the geographic domain, defined by $C=c_1, c_2, \dots, c_n$.

By using the previous definitions, we are able to build the concepts frequency table in the domains, which contains all the domains that can be submitted in the ontology O , and also the concepts located in each domain (see Table 2).

In order to simplify the notation of the concepts, we defined a function that relates to a concept with the identification number of the domain, as well as the index of the concept at the same domain. The function *concept* receives two parameters, which describes the number of the domain and the number of the concept, returning the number of the interest concepts. Otherwise, it returns a Boolean

value ("false") when there is not any concept. The function *concept* is defined as follows: $concept(d, c) = c_{j,k} | 0 \leq j \leq m, 0 \leq k \leq n$.

3.1.3.3. The synonyms domain table. This table allows us to know the possible *alias* that the particular domain could have and the direct relationship with its search (see Table 3). Therefore, let S_i be the set of synonyms for a specific domain d_i , which is defined by $S_i = \{s_{(i,1)}, s_{(i,2)}, \dots, s_{(i,n)}\}$.

3.1.3.4. The composition table of topological relations. In order to semantically process the geospatial information, it is necessary to obtain the set of topological relations that are directly involved between geographic objects in each domain for defining their relevance. The goal to process these relationships is based on describing the behavior or interaction of those objects, because the semantics is implicitly defined in the topological relations (Kurata & Egenhofer, 2006; Budak Arpinar et al., 2006; Euzenat, Gomez-Perez, Guarino, & Stuckenschmidt, 2002). According to the above, the generation of a composition table of topological relations is proposed. This table is ordered, considering its relevance inside of some particular domain. The composition table is presented in Table 4.

Now, let r_t be a relationship of the composition table, which is integrated by the concepts c_i and $c_j, c_j \in C$ and $r_t \in R$, denoted by $r_t = c_i r_t c_j$.

Table 2
The frequency table of concepts in the domains.

Domain	Concepts
D_1	$C_1 = \{c_{(1,1)}, c_{(1,2)}, \dots, c_{(1,n_1)}\}$
D_2	$C_1 = \{c_{(2,1)}, c_{(2,2)}, \dots, c_{(2,n_2)}\}$
D_3	$C_1 = \{c_{(3,1)}, c_{(3,2)}, \dots, c_{(3,n_3)}\}$
...	...
D_m	$C_1 = \{c_{(m,1)}, c_{(m,2)}, \dots, c_{(m,n_m)}\}$

Table 3
The synonyms domain table.

Domain	Concepts
D_1	$S_1 = \{s_{(1,1)}, s_{(1,2)}, \dots, s_{(1,n_1)}\}$
D_2	$S_1 = \{s_{(2,1)}, s_{(2,2)}, \dots, s_{(2,n_2)}\}$
D_3	$S_1 = \{s_{(3,1)}, s_{(3,2)}, \dots, s_{(3,n_3)}\}$
...	...
D_m	$S_1 = \{s_{(m,1)}, s_{(m,2)}, \dots, s_{(m,n_m)}\}$

Table 4
The composition table of topological relations.

Domain	Relevance labels		
	Necessary	Common	Rare
$D_{t,1}$	NE_{D1}	CO_{D1}	RA_{D1}
$D_{t,2}$	NE_{D2}	CO_{D2}	RA_{D2}
$D_{t,3}$	NE_{D3}	CO_{D3}	RA_{D3}
...
$D_{t,m}$	NE_{Di}	CO_{Di}	RA_{Di}

Table 5
The semantic refinement table.

Input labels	Output domains
$E_1=\{e_{11},e_{12},\dots,e_{1n}\}$	$output_1=(D)$
$E_2=\{e_{21},e_{22},\dots,e_{2n}\}$	$output_2=(D)$
$E_3=\{e_{31},e_{32},\dots,e_{3n}\}$	$output_3=(D)$
...	...
$E_m=\{e_{m1},e_{m2},\dots,e_{mn}\}$	$output_m=(D)$

Let N be the set of *necessary relationships* presented in the geographic domain i , where the presence of those relationships in the domain indicates that they are always linked to interact in a particular domain $N_{Di}=\{r_{tN1},r_{tN2},\dots,r_{tNn}\}$.

Let C be a set of *common relationships* presented in the geographic domain i , where the presence of those relationships in the domain indicates that those concepts are commonly found in a particular domain, such that $C_{Di}=\{r_{tC1},r_{tC2},\dots,r_{tCn}\}$.

Let RA be a set of *rare relationships* presented in the geographic domain. Their presence in the domain establishes that is unlikely to find them in the domain. However, it is sometimes possible to find it out in very particular domains. Therefore, the set is defined as follows: $RA_{Di}=\{r_{tRA1},r_{tRA2},\dots,r_{tRAn}\}$.

The domain of composition table D_{ti} is composed of the union of the sets N_{Di} , CO_{Di} and RA_{Di} , which is denoted by $D_{ti}=\{N_{Di}\cup CO_{Di}\cup RA_{Di}\}$. After obtaining the composition table, we proceed to rank the concepts and their topological relations, according to their relevance in the domain. It points out that relationships of the set N are a fundamental feature to define the domain. Thus, the common relationships are not fundamental features, because they could have less relevance in the definition of the domain, such that it is not a requirement to count with those ones. Similarly, the relationships of the set RA , are not indispensable for defining the geographic domain; in addition, their relevance is below of the set C and it has also less relevance than the set N .

In consequence, the function relevant is defined. It receives a triplet that is composed of a pair of concepts and a geographic domain. These items describe the number of domains and the number of the concepts, in the case of the triplet, it returns as result the relevance relationship of the triplet of our interest, which could be “necessary”, “common” or “rare”. The function is defined by the following expression:

$$relevant(d, c_a, c_b) = \begin{cases} true & r_{ij} = \{necessary, common, rare\} \\ false & r_{ij} = \emptyset \end{cases}$$

3.1.3.5. The semantic refinement table. This table is defined to store the labels that are received as the input of the method in order to validate the algorithms proposed in the inference stage. Thus, the labels are assigned to a specific domain, after applying some qualitative spatial reasoning algorithms. This is done, when there is a validation performed by the user (see Table 5).

According to above, let *return_ref* be a function that receives set of input labels $E_i=\{e_{11},e_{12},\dots,e_{1n}\}$, which semantically describe either one or more specific domains, returning as a result a set of ordered output domains, considering the closeness defined by the semantic similarity with respect to the labels description defined

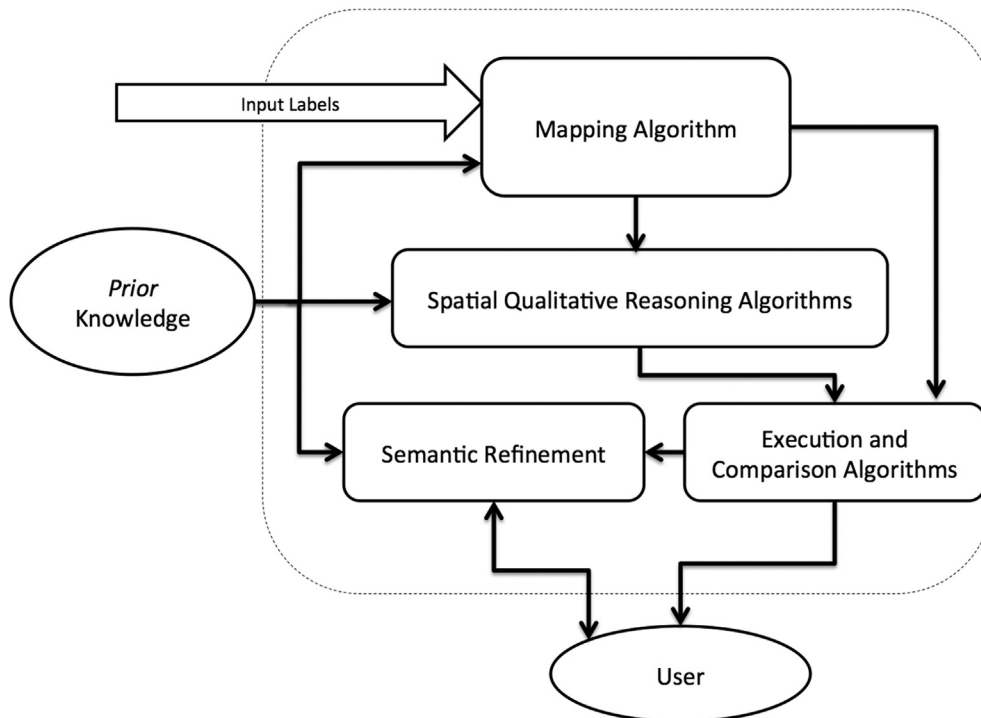


Fig. 7. Conceptual framework of the inference stage.

by $Exit(D)$. Therefore, the function is defined as follows:

$$return_ref(E_i) = \begin{cases} true & Exit(D) \\ false & 0 \leq i \leq m \\ & dof \end{cases}$$

3.2. The inference stage

The inference stage is composed of four tasks that interact together to analyze, describe and deduce which domain belongs to a set of geographic objects represented by labels. The first task

localize if there are concepts related to those labels in order to automatically store or populate in the ontology as instances of a concept class (synthesis process). However, it is necessary to verify if there is a previous result for this set of labels, using the semantic refinement table. A set of existing inputs inside the *a priori* knowledge, or a set of ordered domains D is obtained with this approach. In case that labels have already been previously added and assessed by the user, they will be stored as a part of the conceptualization in ontology O . The algorithm to perform the mapping is presented in Algorithm 1.

Algorithm 1 The mapping algorithm

Input: A set of labels that represents geographic objects $EtE = \{ete_1, ete_2, \dots, ete_n\}$, a table T_c of concepts and a semantic refinement table T_{re}

Output: A mapping vector VM composed of a flag SC that takes a Boolean value, a set of input concepts $CE = \{ce_1, ce_2, \dots, ce_n\}$ when SC is false or a set of ordered domains $D = \{d_1, d_2, \dots, d_n\}$ when SC is true

```

SC ← false
if return_ref(EtE) then
    SC ← true
    return(SC, D)
else
    foreach  $c_i \in C$  where  $1 \leq i \leq n$  do
        if exist_concept( $c_i$ ) then
            |  $c_i \rightarrow ce_i$ 
        else if exist_synonymous( $c_i$ ) then
            |  $c_i \rightarrow ce_i$ 
        end
    return(SC, D)
end

```

consists of establishing a mapping approach, which receives a set of labels as an input. This set is used to search a concept defined in the ontology and that is directly related to those labels. Later, concepts that have been mapped and related to the knowledge base in the ontology are obtained. The second task consists of defining a set of qualitative spatial reasoning approaches, which are determined by three algorithms: (1) conceptual frequency, (2) relevance, and (3) semantic genealogy.

These algorithms carry out the inference process, considering as an input a set of concepts described in the ontology (knowledge base). The third task is proposed to define a comparison of the algorithms, based on the results of applying each method according to the degree of effectiveness, which could change with the user interaction.

Finally, the *semantic refinement* task consists of providing an answer to the user, taking into account a validation process, in which the feedback plays an important role to examine the semantic richness of the representation. The obtained inference is stored in the knowledge base to be part of the conceptualization and determine the degree of effectiveness of the reasoning algorithm. In Fig. 7, a conceptual framework of inference stage is depicted.

3.2.1. The mapping approach

It is an algorithm designed to receive the input labels and

3.2.2. The qualitative spatial reasoning approaches

We propose three algorithms in order to perform qualitative spatial reasoning. The *conceptual frequency* approach is in charged of counting the occurrences of each concept in a geographic domain. The *relevance* approach searches the relationship that exists between the concepts, which are received as input, and their importance in the geographic domain. The *semantic genealogy* approach consists of obtaining the father concepts, computing the hierarchy of concepts that involves to a geographic object represented by the domain.

3.2.2.1. The conceptual frequency algorithm. This algorithm consists of counting the number of occurrences to compute the frequency that each set of concepts appears in a particular domain. This process is called conceptual frequency.

In this algorithm the output is sorted from the highest to the lowest value, according to their repetitions. It receives concepts that have been previously verified by means of the mapping algorithm. This guarantees that the set of concepts is stored in the knowledge base.

Later, it is necessary to use the concepts frequency table in the domains in order to search how many times each concept appears in each geographic domain that contains the knowledge base. In Algorithm 2, the conceptual frequency algorithm is presented.

Algorithm 2 The conceptual frequency algorithm

Input: A set of concepts $CE = \{ce_1, ce_2, \dots, ce_m\}$ that exists in the ontology O , a conceptual frequency table Tf , and a mapping vector VM

Output: A set of ordered domains $D = \{d_1, d_2, \dots, d_n\}$, if SC is true.

$DomainFrequency \leftarrow \{fd_1, fd_2, \dots, fd_n\}$

foreach $fd_i \in DomainFrequency$ **do**
 | $fd_i \leftarrow 0$
end

if SC is false **then**
 | **foreach** $d_i \in D$ where $1 \leq i \leq n$ **do**
 | | **foreach** $ce_j \in CE$ where $1 \leq j \leq m$ **do**
 | | | **if** $concept(d_i, ce_j)$ **then**
 | | | | $increment(fd_i)$
 | | | **end**
 | | **end**
 | **end**
 | $sort(DomainFrequency)$
end

3.2.2.2. The relevance algorithm. The relevance algorithm receives three parameters: a set of input concepts, in which if the concepts exist, then they are obtained from the mapping approach, the second is a set of relevance composition table in the domain, and the third is a mapping vector.

This algorithm is used to rank the *importance degree* of the concepts in the domain. It provides the highest semantic richness to the concepts in each particular domain. It also performs a search of all the concepts that are received as input in the relevance composition table of each domain. The goal is to know if those concepts are related with others. In Algorithm 3, the relevance algorithm is described for a set of concepts that represent geographic objects.

consists of using the relevance algorithm in order to obtain the domain. In this case, only the first result obtained by the relevance algorithm will be considered. The last task performs a sum of the outputs to show the domain that have appeared most with the given inputs into the relevance algorithm. The result of this algorithm is either a domain or an empty set, indicating that the domain has not been found.

The process of the semantic genealogy algorithm is the following: first, if the mapping vector VM is false, then it receives the input concepts. Consequently, the father class of each one of the input n -concepts is searched. Later, it substitutes the i -th concept by the father concept. The goal is to invoke the relevance algorithm with the new set of labels. The obtained result from the relevance

Algorithm 3 The relevance algorithm

Input: A set of input concepts $CE = \{ce_1, ce_2, \dots, ce_m\}$, that exists in the ontology O , a composition table Tc and a mapping vector VM

Output: A set of ordered domains $D = \{d_1, d_2, \dots, d_n\}$, a set of relevance labels $ERD = \{ERd_1, ERd_2, \dots, ERd_i\}$ for each domain $ERd_i = \{N_{Dti}, CO_{Dti}, RA_{Dti}\}$, where $1 \leq i \leq n$

if SC is false **then**
 | **foreach** $d_i \in D$ where $1 \leq i \leq n$ **do**
 | | **foreach** $ce_j \in CE$ where $1 \leq j \leq m$ **do**
 | | | **foreach** $ce_k \in CE$ where $1 \leq k \leq n$ **do**
 | | | | **if** $relevant(d_i, ce_j, ce_k)$ **then**
 | | | | | $increment \text{ the corresponding label to } ERd_i = \{N_{Dti}, CO_{Dti}, RA_{Dti}\}$
 | | | | **end**
 | | | **end**
 | | **end**
 | **end**
 | $sort(ERD)$
end

3.2.2.3. The semantic genealogy algorithm. This algorithm is divided into three tasks. The first is to search the father and children concepts of each one of the input concepts. The second task

algorithm is stored as the first element obtained in an output vector, which contains the domain with the frequency that such domain is repeated. This process is iterative according to the

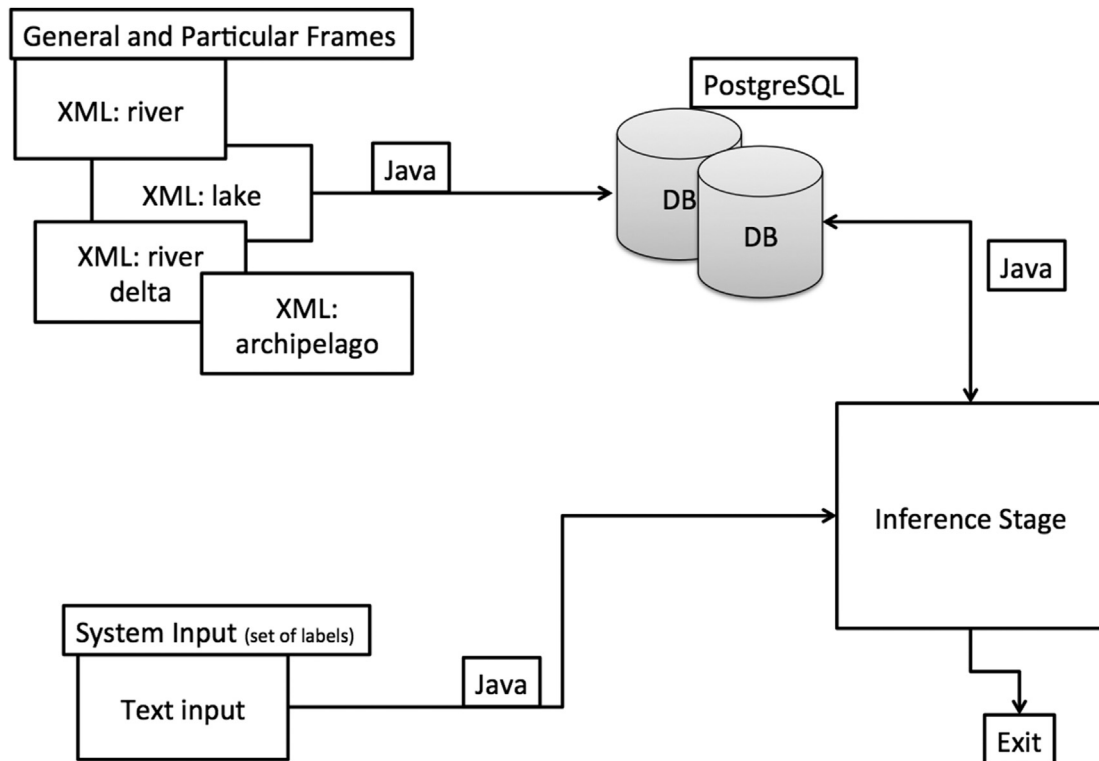


Fig. 8. Architecture of the RAIN system.

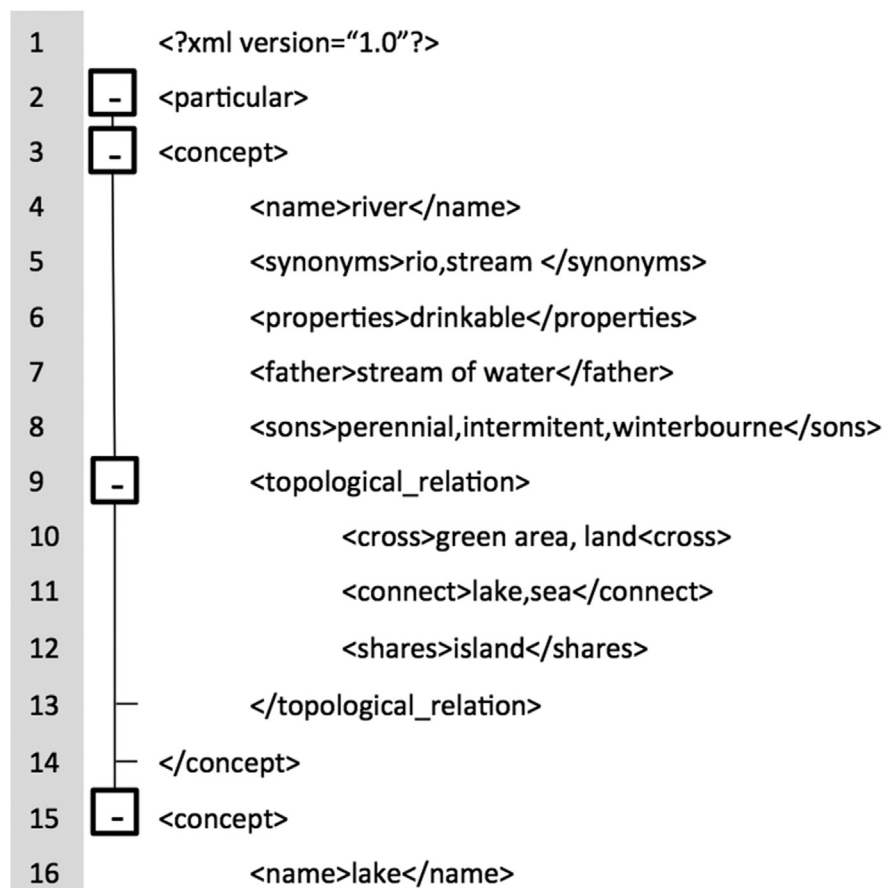


Fig. 9. Conceptual particular framework.

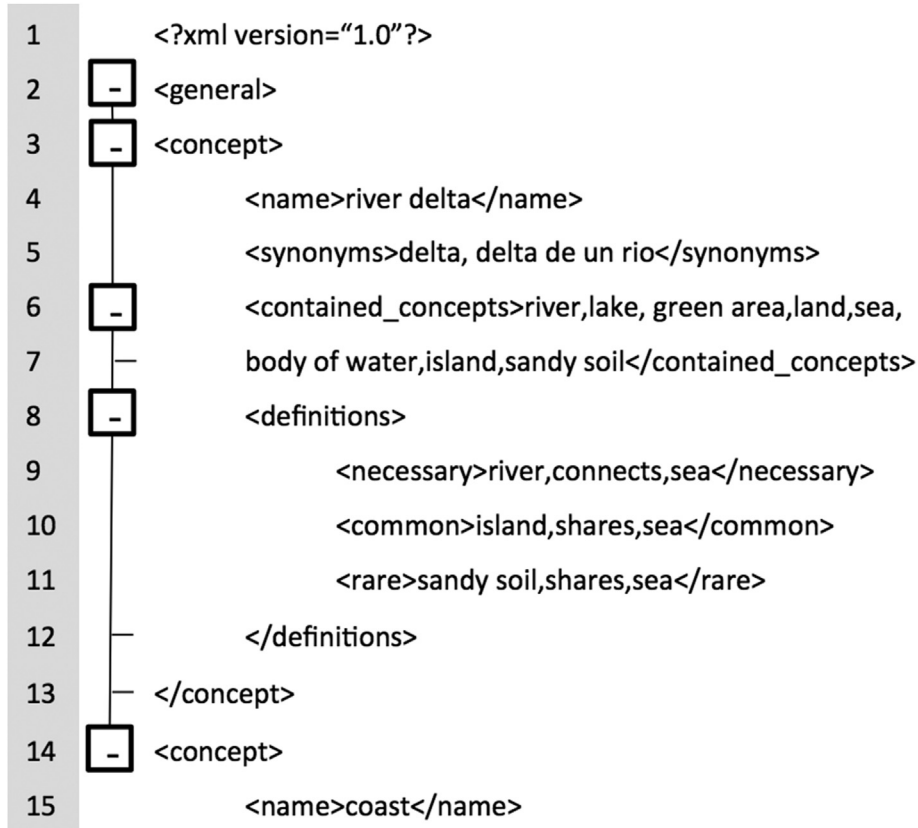


Fig. 10. Conceptual general framework.

number of father concepts that are found in the analysis. The procedure for the children concepts of each input concept is similar, but the difference is that each input concept can have a m number

of children concepts, such that each son concept will be an individual input for the conceptual frequency algorithm. The semantic genealogy algorithm is described in Algorithm 4.

Algorithm 4 The semantic genealogy algorithm

Input: A set of input concepts $CE = \{ce_1, ce_2, \dots, ce_m\}$, that exists in the ontology O , a composition table Tc and a mapping vector VM

Output: A set of ordered domains $D = \{d_1, d_2, \dots, d_n\}$, if SC is true.

if SC is false **then**

foreach i where $0 \leq i \leq n$ **do**

$CE \rightarrow CET$

if $father(cet_i) \neq \emptyset$ **then**

$father(cet_i) \rightarrow cdt_i$

$RelevanceAlgorithm(CET)$

$d_i \rightarrow Domains$

end

end

foreach $son(ce_i)$ **do**

$CE \rightarrow CET$

if $son(cet_i) \neq \emptyset$ **then**

$son(cet_i) \rightarrow cet_i$

$RelevanceAlgorithm(CET)$

$d_i \rightarrow Domains$

end

end

$ReviewRepeatedDomains(Domains)$

$sort(ERD)$

end

4. Experimental results

This section presents the results of applying the RAIN methodology. They are outlined by each stage defined in this work.

4.1. System architecture

The architecture of the system is depicted in Fig. 8. It is composed of three elements. The first is the repository where the conceptual frameworks are processed. The second is in charge of loading the persistent model of database, which is built from the ontology. The third is the input of the system that is directly related to the inference stage. It consists of querying information of the persistent model in order to return the general concept to a certain domain or geographic context.

4.2. Conceptual frameworks

In order to represent the knowledge, we propose conceptual frameworks as a basic structure, which are able to be readable by a machine. In this work, we have chosen the use of conceptual frameworks described in (Minsky, 1974, 1980). The implementation

of these structures is based on XML meta-language (Zambon & Sekler, 2007), because according to its structure, it is possible to carry out a hierarchical classification and organization of the *a priori* knowledge. The proposed conceptual frameworks are divided into two types: particular and general.

The *conceptual particular framework* (see Fig. 9) contains information of the concepts that directly integrate and represent a specific geographic domain, with data that correspond to the name, synonyms, father and children concepts.

The *conceptual general framework* (see Fig. 10) is based on definitions of a given domain by means of the topological relations, which exist between concepts that describe the domain and their synonyms. This type of framework defines a context for the concepts and synonyms that are used in the reasoning task.

4.3. Persistent model of the ontology-based design

The persistent model has been built using the RAIN ontology, in order to store the translation of concepts, relationships and properties, as well as the instances of these items into a repository. It is composed of nine tables that are designed to receive information from the analysis and conceptualization stage by means of the

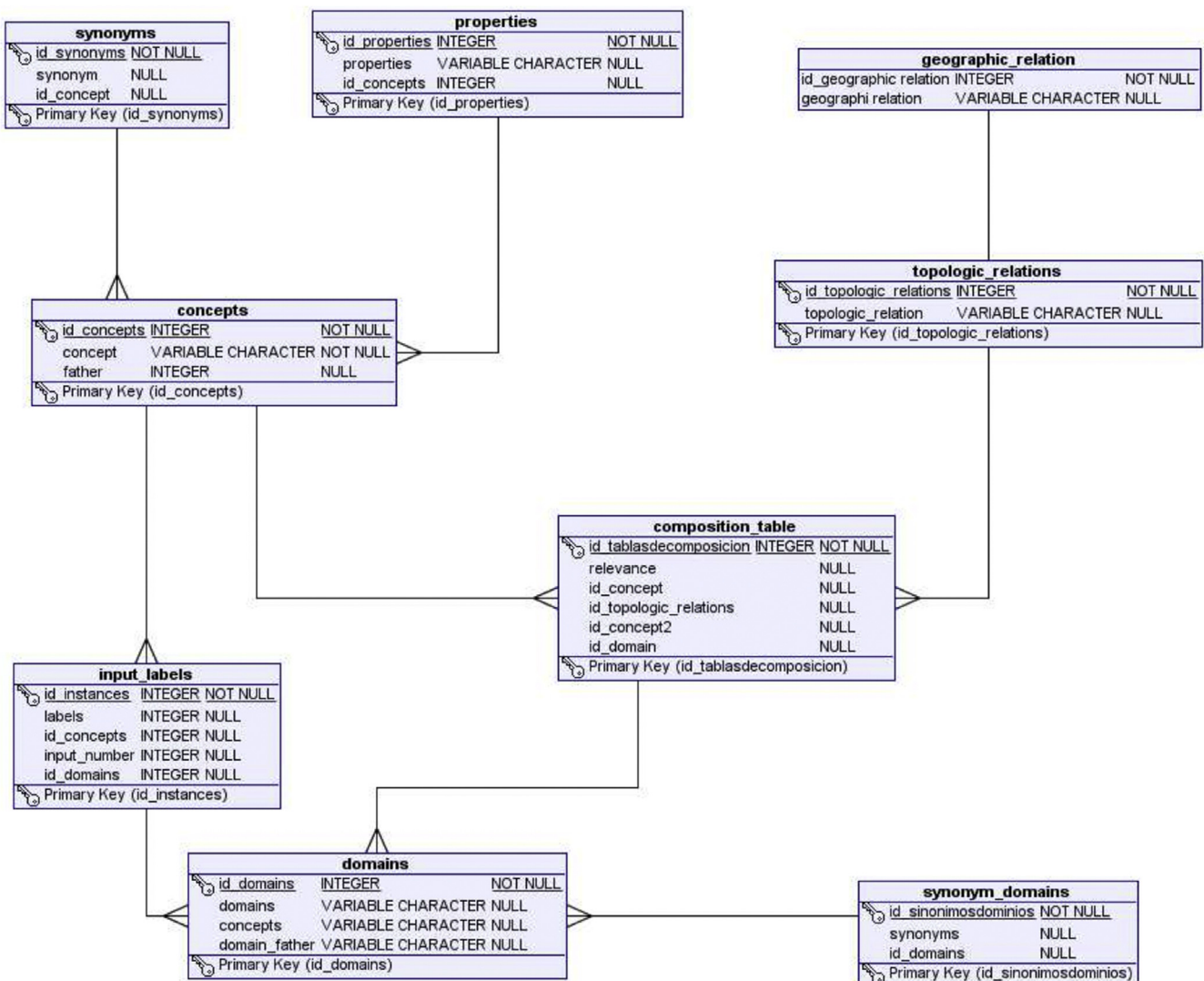


Fig. 11. The persistent model generated from the RAIN ontology.

conceptual frameworks.

The description of tables that compose the persistent model, shown in Fig. 11 is the following: the concepts table, which contains information related to the name of the concept, location in the hierarchy (father and children). The synonyms table stores information about the known names of the concepts. The table of properties contains the characteristics of each concept. The

composition table stores information related to topological relations that are presented between concepts, domain that they belong to, and the level of relevance inside the domain (necessary, common and rare relationships). Finally the table of input labels contains information of the labels that is received by the inference stage.

As we have mentioned above, the model is built considering the

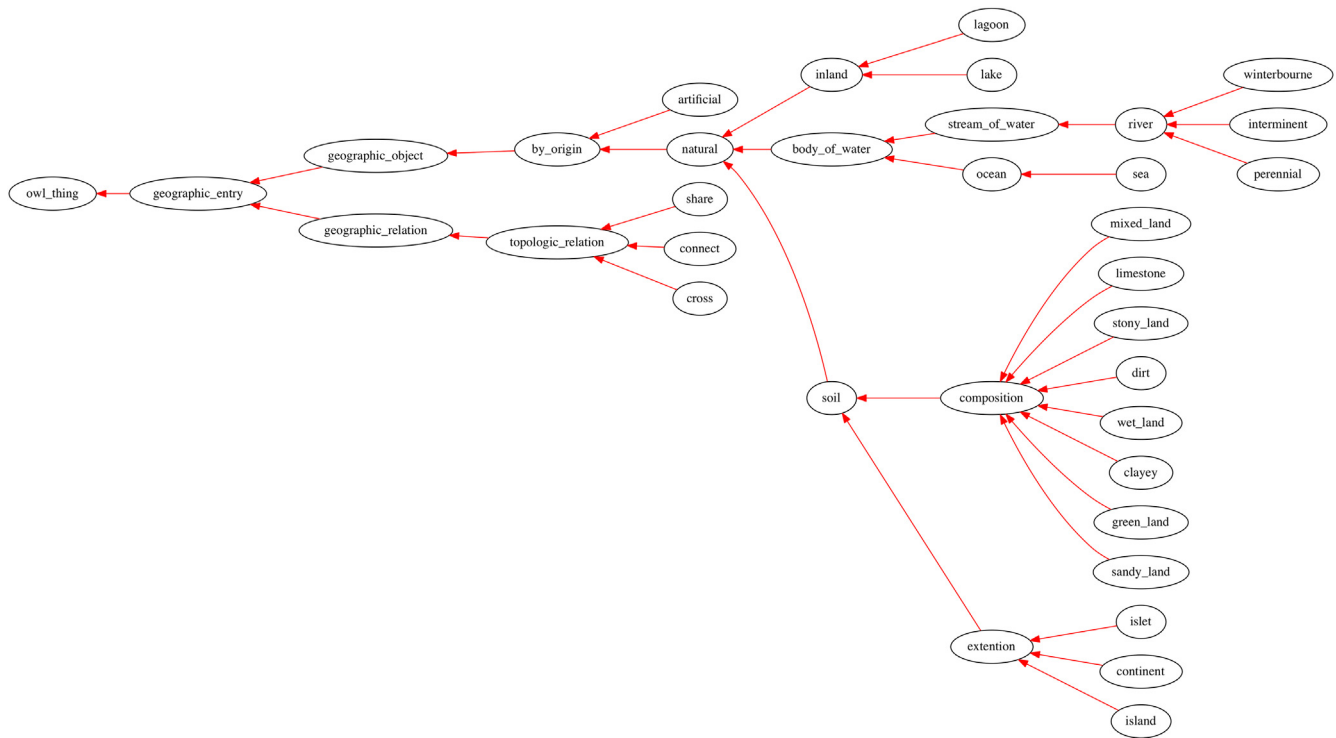


Fig. 12. The main hierarchy of classes in the RAIN ontology.

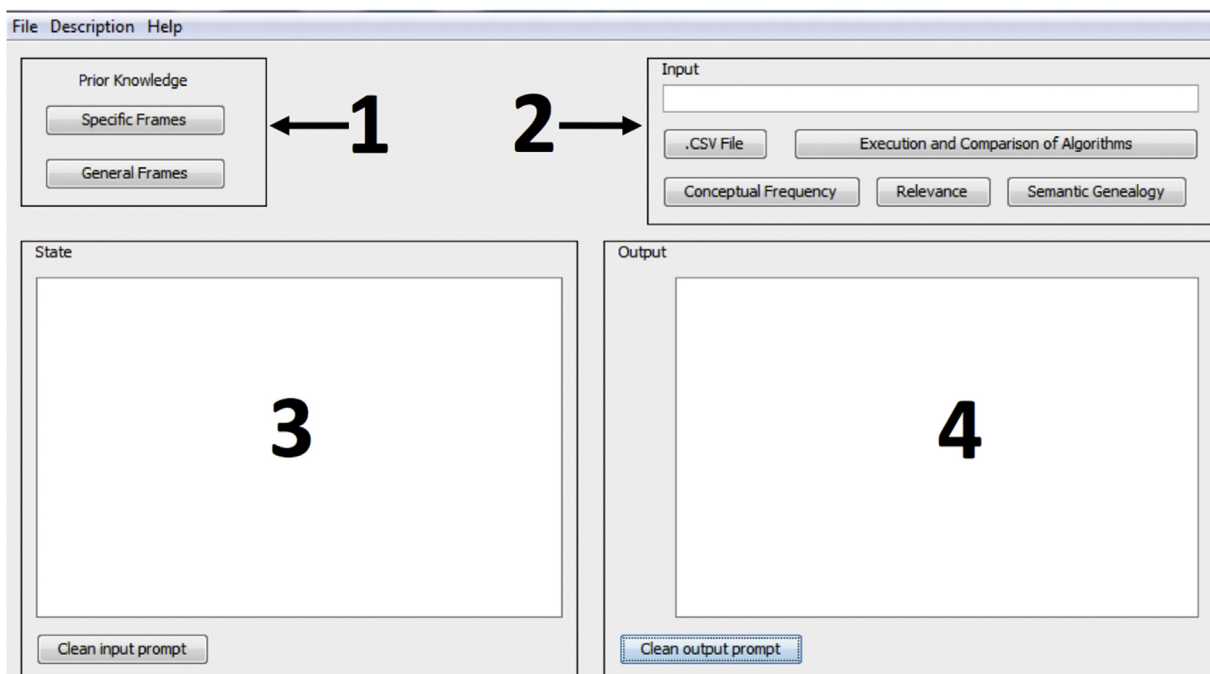


Fig. 13. The RAIN application.

RAIN ontology (see Fig. 12). The RAIN ontology describes the definition of concepts and topological relations that represent geographic objects and their behavior among them inside the geographic domains. This ontology is also implemented according to the *Kaab* ontology and using the GEONTO-MET methodology for its building (Torres et al., 2011).

4.4. The RAIN application

The RAIN application is composed of four elements, which are depicted in Fig. 13. The first element points out the input of the system to introduce the *a priori* knowledge, using the conceptual frameworks (see number “1”). The second element (see number “2”) is the input to add the set of labels in order to infer the domain that labels belong to. In this section, the algorithms to apply qualitative spatial reasoning and the method for comparison the results are located. The third element (see number “3”) shows the operations that are performing over the repository. The forth element

and *coast*. First, we load the *a priori* knowledge to the repository of the RAIN application, using both conceptual frameworks (identified by number “1”). In Table 6, the frequency of each concept for the mentioned domains is presented.

Therefore, the input labels used in the test are the follows: <sea, sandy land, river, island, green area>. The output obtained was <river delta>, because it was the domain with more occurrences and in the second place the domain was <coast>, with 3 concepts in this domain. In Fig. 14, the result of conceptual frequency algorithm is depicted. We can appreciate the number of occurrences directly from the ontology in each domain per concept.

However, this approach presents a problem that is directly related to the domains. When the user introduces labels that are located in both domains (i.e., <sea, sandy land>), the same output is obtained. In order to solve the ambiguity, a distinction among the label is performed, taking into account the importance degree inside the domain. Thus, the *relevance algorithm* is proposed to solve the repetitions of occurrences. It considers the definition of the concepts according to their topological relations that are implicitly involving them. The composition of topological relations is presented in Table 7.

Now, it is possible to repeat the test when the user introduces <sea, sandy land>. When the relevance algorithm is applied, the first obtained domain is <coast>, followed by <river delta>. The fact is that definition of each one of the domains, both concepts exist, but only in <coast>, a necessary relationship is

Table 6
The table of concepts frequency.

Domain	Frequency	Output
River Delta	7	{river, lake, green area, land sea, body of water, island, sandy land}
Coast	3	{sea, sandy land, river}

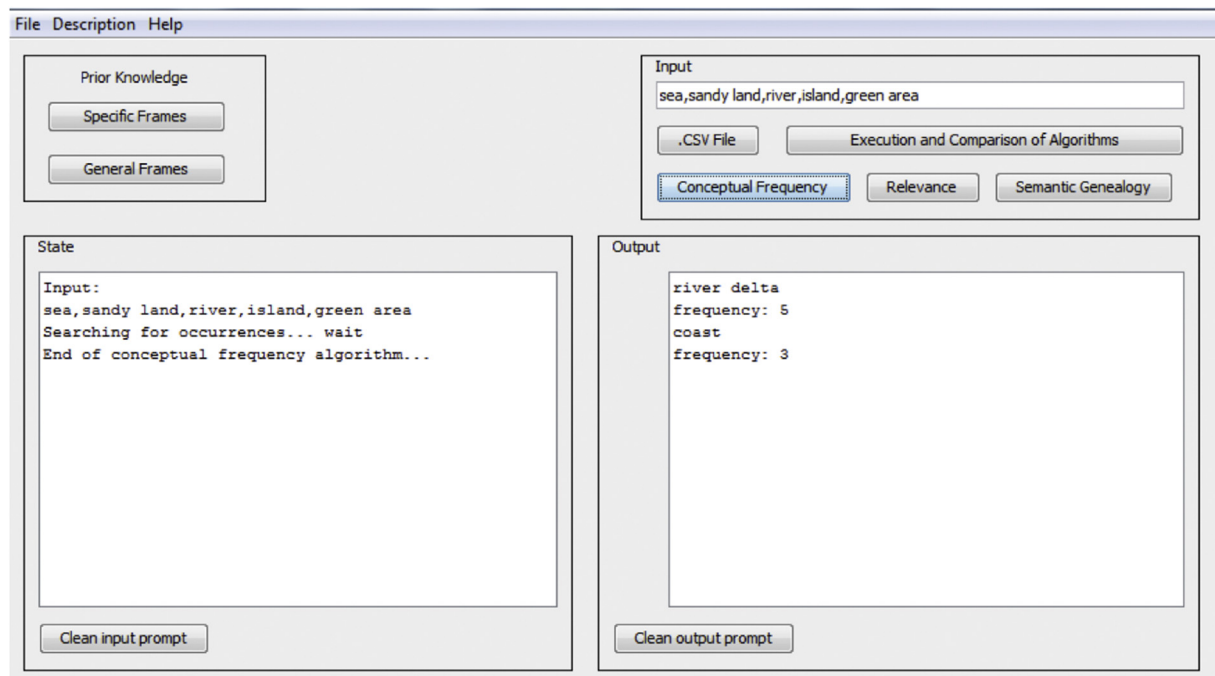


Fig. 14. Results of the conceptual frequency algorithm.

(see number “4”) presents the results obtained by the RAIN application, depending on the selected algorithm.

4.5. Test and results obtained by the qualitative spatial reasoning algorithms

This test presents the results obtained by applying the *conceptual frequency algorithm*, using the geographic domains *river delta*

Table 7
The composition table of topological relations.

Domain	Concept	Topological relation	Concept	Relevance
River Delta	River	Connect	Sea	Necessary
River Delta	Island	Share	Sea	Common
River Delta	Sandy land	Connect	Sea	Rare
Coast	Sandy land	Connect	Sea	Necessary
Coast	River	Cross	Green area	Common
Coast	River	Connect	Sea	Common

presented, which is defined by “sandy land shares sea”, whereas the relevance in the domain of “river delta is less”. It is unusual to find this kind of relationship in that domain or context. In Fig. 15, the result of applying the relevance algorithm is shown.

On the other hand, when the user introduces concepts that are not explicitly defined in the domains; for instance, let <perennial, sea> be input labels, where “perennial” belongs to subclass of “river”, the *semantic genealogy algorithm* is used in order to search the father of that concept and subsequently execute the relevance algorithm for obtaining the result. Moreover, it is necessary to search the children classes and verify whether those definitions exist. The final step consists of repeating this procedure for the concept “sea”. In Fig. 16, the results of applying the semantic

genealogy algorithm is depicted.

In Table 8, we present the summary with respect to the results obtained from the three qualitative spatial algorithms. We can appreciate that the best result is generated by the *relevant algorithm*, because it has three correct answers with respect to the other algorithms. The reason is that it considers the topological relations between the geographic concepts in order to infer the domain. The *semantic genealogy algorithm* produces acceptable inferences, because it establishes the neighborhood in the ontological hierarchy of the concepts (father and children). The *conceptual frequency* is the algorithm that presents problems, when some labels are located in both domains, because the occurrence of the concepts does not determine in an adequate way the domain for a set of

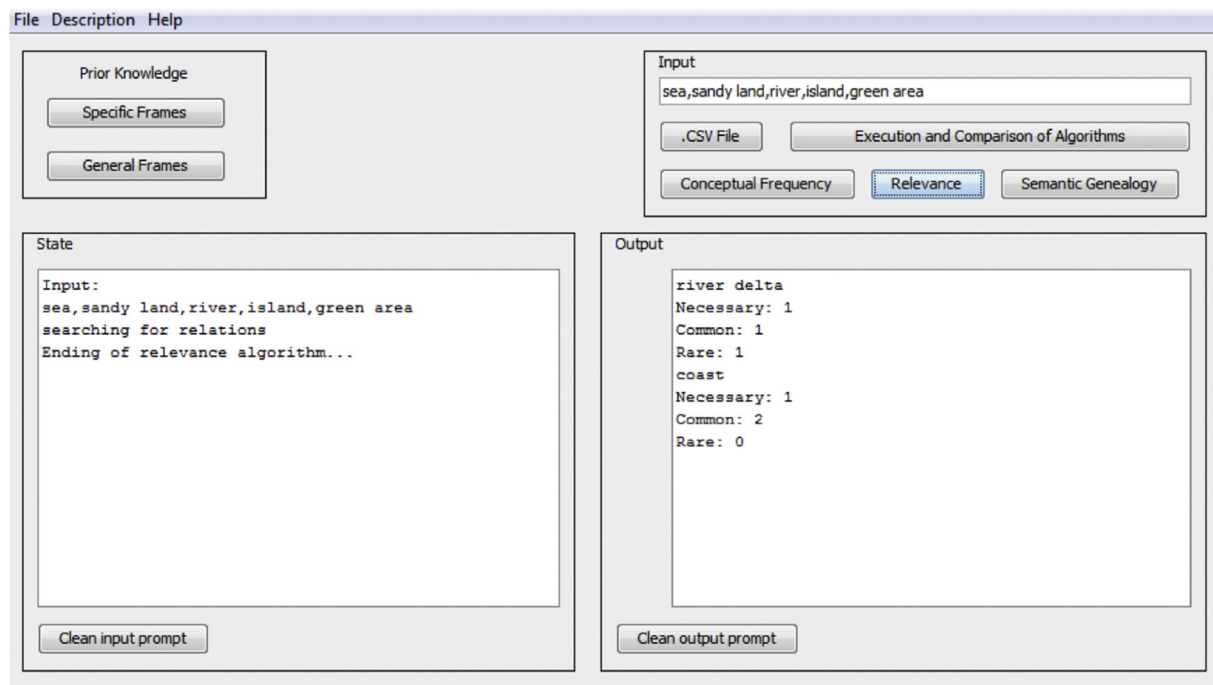


Fig. 15. Results of the relevance algorithm.

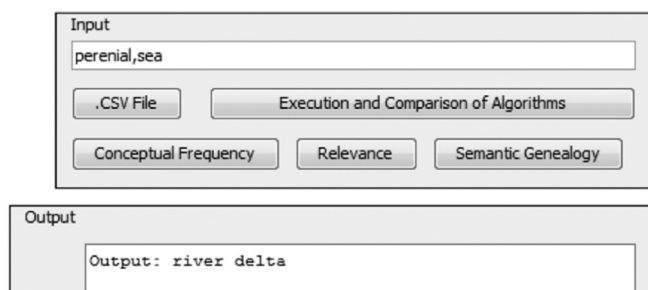


Fig. 16. Results of the semantic genealogy algorithm.

labels. In Fig. 17, the process to compare and validate the results of the three algorithm is depicted.

5. Conclusion and future works

In this work, a methodology mainly composed of three approaches to carry out an inference process is described. These approaches are focused on performing qualitative spatial reasoning into geographic objects descriptions.

Thus, a knowledge base is generated by means of application ontology, which has been built in OWL, using the GEONTO-MET methodology. This conceptual structure represents the *a priori*

Table 8
Comparison of the qualitative spatial reasoning algorithms.

Input labels	Conceptual frequency	Relevance	Semantic genealogy	Correct inference
<Sea, sandy land>	River delta, Coast	Coast	No results	Coast
<sea, sandy land, river, island, green area>	River delta	River delta	Coast	River delta
<River, sea>	River delta, Coast	River delta	No results	River delta
<Perennial, sea>	River delta, Coast	No results	River delta	River delta
<Composition, sea>	River delta	No results	Coast	Coast

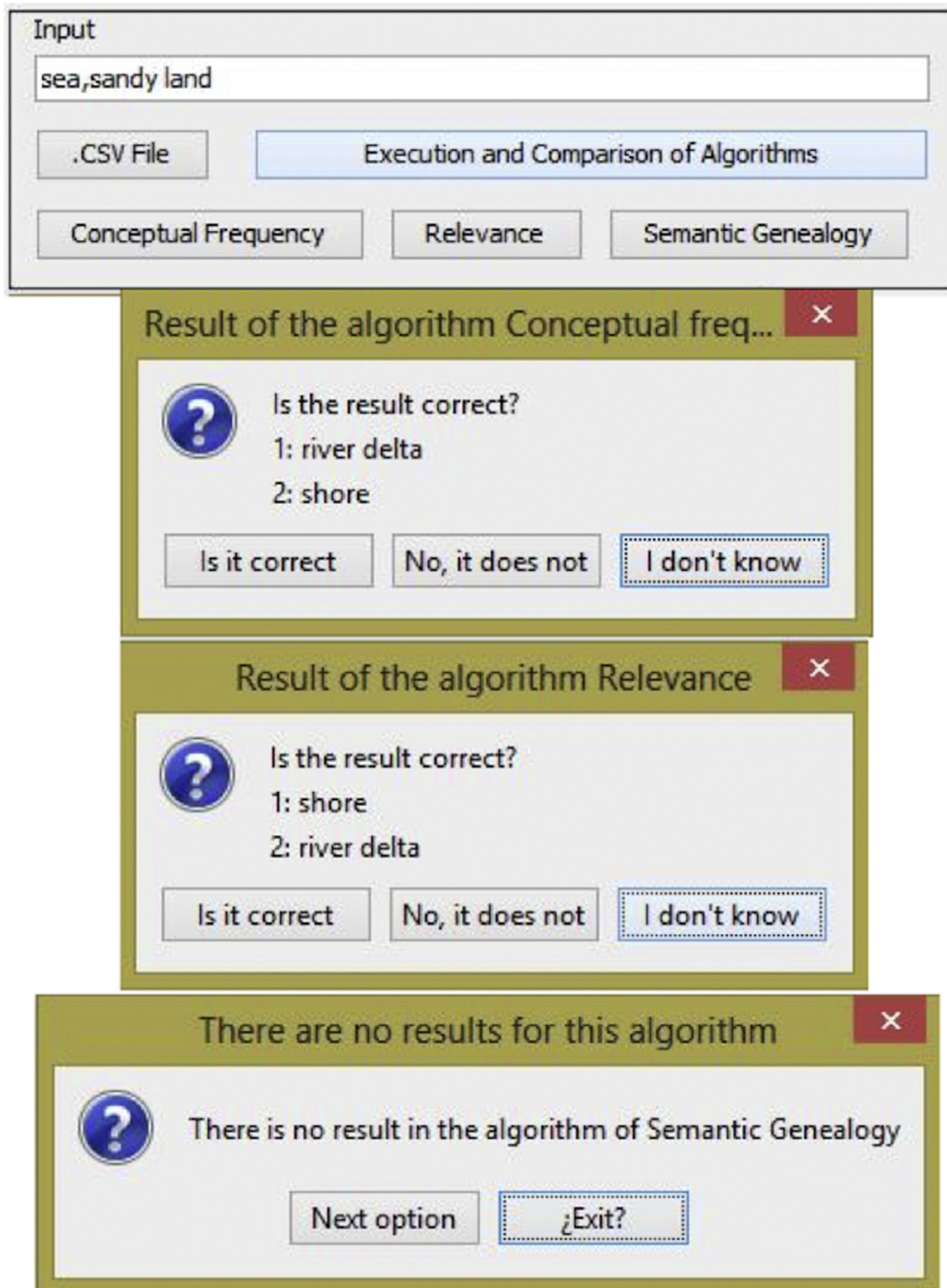


Fig. 17. Comparison and validation process of the qualitative spatial algorithms.

knowledge of different geographic domains. Moreover, we propose the use of conceptual frameworks to represent explicitly the knowledge of any domain, in order to structure and organize the semantics of the geographic context. These frameworks describe the synonyms, names, relationships, properties and other characteristics related to geographic objects of any particular geographic domain.

We argue that any qualitative spatial reasoning algorithm consists of two tasks: 1) a searching task and 2) a ranking task based on the relevance of the characteristics or relationships. In addition, we

assert that *a priori* knowledge is a formal structure, which contains the vocabulary, rules for the language and a set of logical propositions that allow us to fundamentally solve problems associated to ambiguity, uncertainty and vagueness of the geographic data.

The inference stage depends directly on particular data that are stored in the conceptual frameworks, which is denoted by *a priori* knowledge. In fact, the qualitative spatial reasoning algorithms are complementary to each one. The best result is provided by the relevance approach, because it considers *a priori* knowledge such as the topological relationships and properties defined in conceptual

frameworks. The semantic genealogy is iterative in order to consider the execution of the conceptual frequency and relevance approaches. In the case that the knowledge is not defined in the conceptual framework, it would not be possible to infer about the conceptual structure for determining the concepts and their interaction in a particular domain.

Moreover, a definition of spatial reasoning is proposed. It consists of transforming a descriptive representation in another more general, taking into account the semantics of the topological relationships. It is important to note that the process performed in this work, attempts to generalize toward a superior class or concept in an inverse sense to the semantic granularity that is defined by a conceptual representation, whereupon a machine can process the geographic entities, in a similar way that we as human beings cognitively process and understand the real world in a generalized manner. This fact is implicitly related to compare the results obtained by our approach. According to the above, we consider that the best evaluation is performed by a domain expert, who has the knowledge to say if the inferred results are coherent and precise.

Future works are focusing on making more tests in different geographic domains as well as other totally different contexts. It is necessary to compare the inferred results provided by our methodology with other semantic reasoners such as Pellet, DLog, OWL-DL, RacerPro, Cyc, FaCT++, etc., in order to evaluate different results and compare them, computing the same tests in such reasoners. Other work is oriented towards enriching the conceptual frameworks as well as the application ontology with more geometric, direction and mereological relationships for improving the inference approaches, considering more semantic granularity to generalize concepts and determine a specific domain.

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