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RESEARCH ARTICLE

Formalizing spatiotemporal knowledge in remote sensing applications to improve image interpretation

Christelle Pierkot, Samuel Andrés, Jean François Faure, and Frédérique Seyler

UMR Espace-Dev, 34093 Montpellier, France

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Abstract: Technological tools allow the generation of large volumes of data. For example satellite images aid in the study of spatiotemporal phenomena in a range of disciplines, such as urban planning, environmental sciences, and health care. Thus, remote-sensing experts must handle various and complex image sets for their interpretations. The GIS community has undertaken significant work in describing spatiotemporal features, and standard specifications nowadays provide design foundations for GIS software and spatial databases. We argue that this spatiotemporal knowledge and expertise would provide invaluable support for the field of image interpretation. As a result, we propose a high level conceptual framework, based on existing and standardized approaches, offering enough modularity and adaptability to represent the various dimensions of spatiotemporal knowledge.

Keywords: spatiotemporal metamodel, geographic standards, remote sensing interpretation, image and field viewpoints, ontologies, knowledge representation, spatial reasoning

1 Introduction

Technological tools allow the generation of huge volumes of data, such as satellite images, helping the study of spatiotemporal phenomena in various research fields, such as environmental monitoring, health care, or ecological surveying. However, at this point, few remote-sensing interpretation tools used by experts actually associate content of satellite images (e.g., color, texture) with knowledge of the study of area (e.g., mangrove characteristics) [4,23,29]. Moreover, this software poorly integrates the spatiotemporal aspects to be considered in order to make meaningful interpretations. Thus, experts generally proceed by trial and error to build semantic interpretations of these images, leading to a lack of unified results (two experts will probably make different interpretations of the same image because they do not have the same knowledge of the reality of field). Therefore, it is necessary to propose solutions that will allow the most efficient and appropriate interpretation of satellite images, regardless of the focus of the scientific knowledge area.

To improve the semantic interpretation of satellite images, we argue that two perspectives must be taken into account: the *image point of view* which is dedicated to describe the characteristics of the object in the image (e.g., texture, wavelength, ...), and the *field point of view* which is used to describe the properties of the feature in the field reality (e.g., leaf type, . . .). Furthermore, because spatiotemporal aspects are intrinsically linked to both physical objects or geographical features (e.g., mangrove is spatially distributed and has spatial and temporal relationships with ocean and coastal areas, an image segment is defined by a shape and maintains spatial relationship with other segments), we believe that spatiotemporal dimensions can be a foundation to unify knowledge from these two perspectives. Moreover, we hold that the spatiotemporal expertise acquired by the GIS community would provide invaluable support to the field of image interpretation [1,8,12,14,33]. Thus, we propose to formalize the spatiotemporal knowledge used in image interpretation process, by relying on work from GIS community and standards specifications.

As a result, a high-level conceptual metamodel has been applied, offering enough modularity and generality to give a standardized semantic description of the spatiotemporal knowledge. This metamodel can then be formalized into a framework ontology, used to design domain ontologies according to specific application contexts and objectives (e.g., urban planning or land cover mapping).

This paper is structured as follows. Firstly, we discuss the spatiotemporal aspects that can be found in the remote sensing interpretation process. In Section 3, we introduce our metamodel based on standards and previous work and we detail each component individually. Section 4 provides an example of the application of the metamodel where it was used to conceptualize both expert knowledge and image representation and where reasoning was made to help the interpretation process. Finally, we conclude and give some perspectives (Section 5).

2 Spatiotemporal aspects in remote sensing interpretations

In the process of image interpretation, image and field are two complementary viewpoints that represent the same features according to different perspectives. For example, according to field and image viewpoints respectively, “mangrove” can be defined by biological properties such as leaf type or the salinity of the environment; or by physical characteristics such as wavelength or texture. Moreover, spatiotemporal information exists in both image and field viewpoints and spatiotemporal concepts are commonly used to define features. For example, the concept of *shape* is used to describe the geometry of a feature in both the image or the field viewpoints. Spatial relationships are also used to define the relative position of features from each other (e.g., mangrove is located *between* ocean and continent in a field; vegetal segment is *between* water and mineral objects in an image). This consideration also applies to temporal characteristics where, for example, information concerning periods in the life of a feature can be seen both in the image (time series) and field (life cycle). Because, spatiotemporal concepts exist in both viewpoints, it seems useful to use them as a common basis for describing the different viewpoints. Thus, we must also take into account the spatiotemporal dimension in the modeling of knowledge.

Some progress has been made to model information with spatial and/or temporal dimensions. However, these approaches were not designed especially to track spatiotemporal phenomena [5], as they are oriented towards only one particular phenomenon [3], or they have been designed for other tools, such as GIS or spatial databases [17, 33].

Otherwise, the GIS community has been very active in modeling spatiotemporal knowledge for many years [1,8,12,14,26,33]. Some of the work has resulted in standard specifications and recommendations from OGC and ISO [24, 31], and has provided design foundations for both GIS software and spatial databases. This expertise would provide invaluable support for the field of image interpretation, so in this paper we rely on these works to formalize the spatiotemporal knowledge used in remote sensing applications.

Nevertheless, it is first necessary to represent knowledge in a common formalism.

3 Spatiotemporal metamodel

The proposed metamodel is intended to be used by those who handle satellite images to make interpretations of spatiotemporal phenomena. The analysis is made in various areas (e.g., land cover, health, biodiversity) by people with different expertise (e.g., ecologist, cartographer) and with distinct objectives (e.g., land cover mapping, phenomena tracking, health monitoring). Thus, the model needs to be easily understood, sufficiently expressive to satisfy all information met in diverse areas, and flexible regardless of the context and objectives.

However, (1) all knowledge must be formalized to be usable; and (2) matching between the image and field viewpoints is necessary to exploit information (e.g., recognize that "mangrove" defined in the field point of view corresponds to a vegetal segment in the image perspective). Thus, the metamodel must also be sufficiently generic to represent the characteristics of distinct viewpoints and sufficiently modular to make matching easier.

As a result, we propose an approach to describe the spatiotemporal knowledge based on conceptual schemas, which are used to give a semantic description of the domain. This metamodel, based on normalized work, is then used as a framework to specify the spatiotemporal knowledge in a particular application context, such as risk analysis, biodiversity indicators, deforestation monitoring, and so forth.

The semantic description can then be used to formalize the spatiotemporal knowledge into a framework ontology. Indeed, specifying a framework ontology will give a common basis for describing the different viewpoints, thereby helping the implementation of bridges between the various elements to be described. This then reduces what is usually called the "semantic gap" [22]. This ontology is used to design domain ontologies according to specific application contexts and objectives (e.g., urban planning or land cover mapping).

In the following section we present our metamodel by focusing on the way we organize the information to consider the geographic standards and integrate major reference work [1,12,24,31].

3.1 Metamodel structure

A general view of our metamodel is presented in Figure 1, where eight components have been identified to define spatiotemporal knowledge in the field of image interpretation. We organize them as UML packages in order to aggregate information semantically close and to ensure modularity.

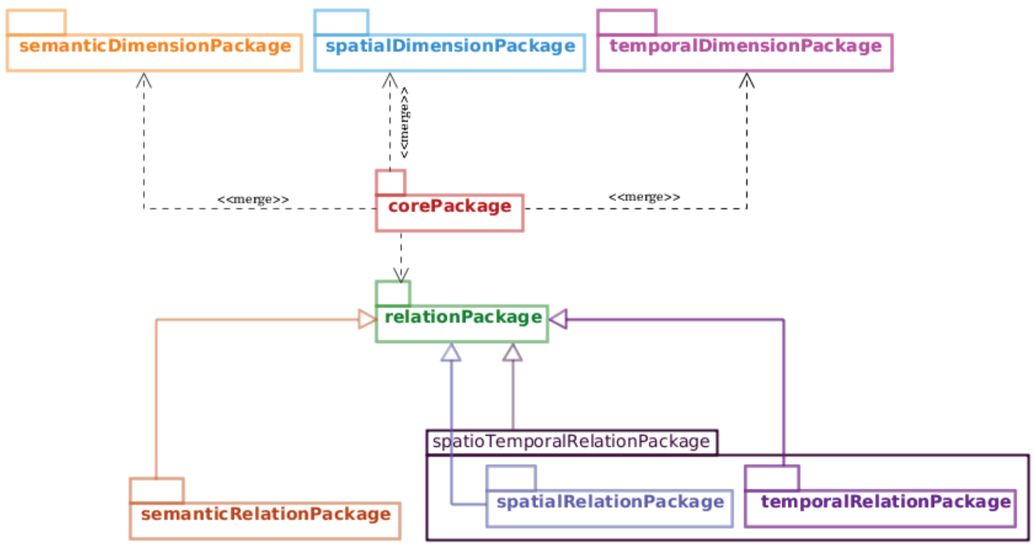

Figure 1: Spatiotemporal packages.

We use the merge directed relationship between the CorePackage and the SpatialDimensionPackage, the TemporalDimensionPackage, and the SemanticDimensionPackage to indicate that the content of the CorePackage can be extended by the elements of the another packages. In another way, we use the generalization relationship between the diverse packages to express that a relationship must be refined in terms of whether it is spatial, temporal, spatiotemporal, or semantic.

3.2 The Core package

The CorePackage is the central element of the metamodel and is linked to other packages by UML dependency relationships (Figure 2).

It is a shared opinion that a geographic feature is an object, which represents an abstraction of a real world phenomenon with a local position from the earth [24, 31, 33]. Thus a geographic feature has a spatial dimension and characteristics defined by attributes. However, modeling geographic features to track spatiotemporal phenomena, such as the decrease of mangrove forest, involves taking into account both spatial and temporal dimensions [15, 34]. Moreover, modeling relationships between geographic features can be helpful in the interpretation process to find distinct objects in an image (e.g., to distinguish that ONE kind of vegetation can be classified as mangrove by knowing that mangrove is currently located between continent and ocean). Thus, we define a geographic feature as: *a whole composed by spatial, temporal and semantic dimensions, with which different kinds of relationship can be specified*.

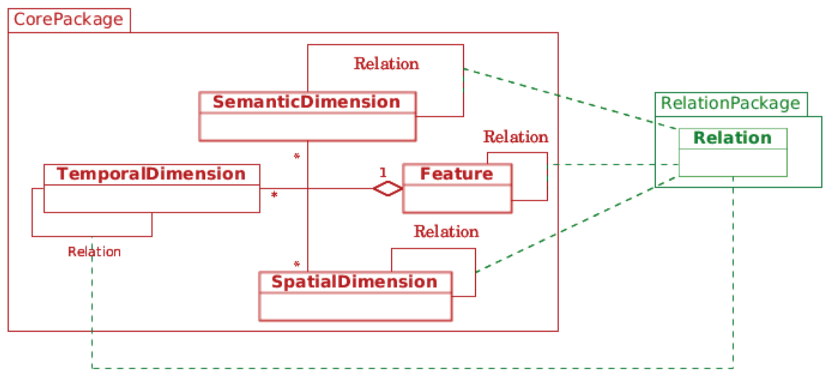

Figure 2: Core package.

The originality of this conceptualization relies on the following points. First, the SemanticDimension, which gives the characteristics of a geographic feature, is defined as a class and not as an attribute of the class feature. Due to this conceptualization, it is possible to take the different points of view associated with one geographic feature into account. For example, in the field viewpoint, the SemanticDimension class describes the relative domain properties of the concept (e.g., mangrove characteristics), while in the image viewpoint, the SemanticDimension class describes the physical properties of the object (e.g., IR spectral band values). Secondly, relationships are specified by each core class (i.e., feature, semantic, and spatiotemporal dimensions) and not only on the geographic feature. Thus, according to the different points of view, we can explicitly specify which element is affected by the relationship. For example, in a remote sensing image (image point of view), the spatial relationship between two objects is generally defined by the geometry, which is a spatial dimension concept. The feature itself will be used by the expert in the field viewpoint. Finally, in contrast to other models, where relationships are defined by a simple UML relation, we have chosen to represent relationships as an association class, which will be reified. The aim here is to be able to add specific information as properties, such as the reference frame used to define a spatial relationship (see Section 3.6.1 for the detail of this property).

3.3 Spatial dimension

The SpatialDimensionPackage contains information about spatial references of the feature (Figure 3).

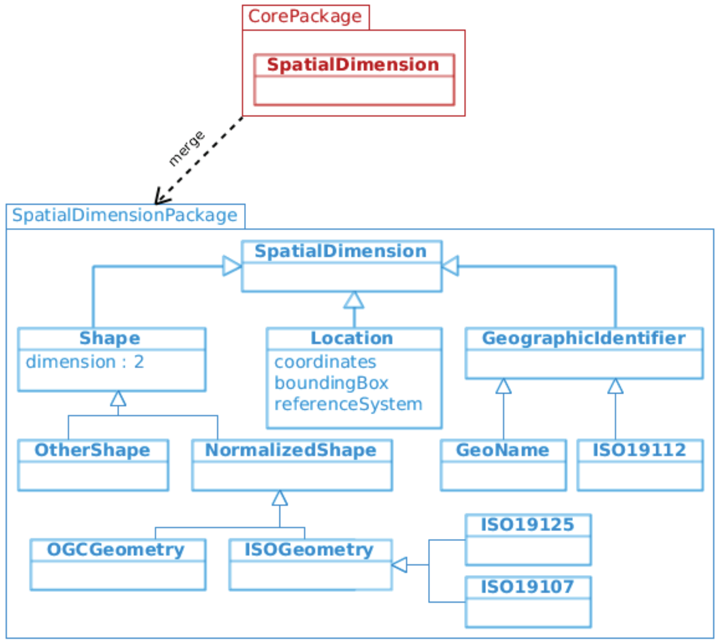

Figure 3: Spatial dimension package.

Usually, the spatial dimension of a feature is defined by a location and a geometric shape [24,33]. The feature position is provided by geographic or planar coordinates or by an approximation, such as a bounding box. However, whatever the representation mode, it is necessary to add the associated geodesic reference system. Following the point-set topological theory defined by [12], many attempts have been made to specify the geometry of a geographic feature, which have been included in the standards (e.g., ISO19107, ISO 19125-1, OGC Features) [24,25,31]. Thus, we add a class NormalizedShape to our metamodel to set the concepts defined in the OGC and ISO standards. However, our approach allows us to describe the shape by concepts taken from the application domain through the class OtherShape. Indeed, in a satellite image, we can extract the feature shape concepts with some classes defined by remote sensing software (e.g., Ecognition or OrpheoToolBox). Finally, spatial referencing can be made by using a geographic identifier defined by the GeographicIdentifier class in our conceptualization. Indeed, it is useful to be able to denote a feature (e.g., "Cayenne's coastal" in the field point of view) which can be transformed in a bounding box that delineates the affected area. However, to reduce the semantic gap induced by the fact that the same feature can be named differently, we intentionally constrain the use of geographic identifiers defined in the ISO 19112 standard [24], or by a geographical concept contained in the *Geoname* database.

3.4 Temporal dimension

The TemporalDimensionPackage includes concepts that characterize time (Figure 4).

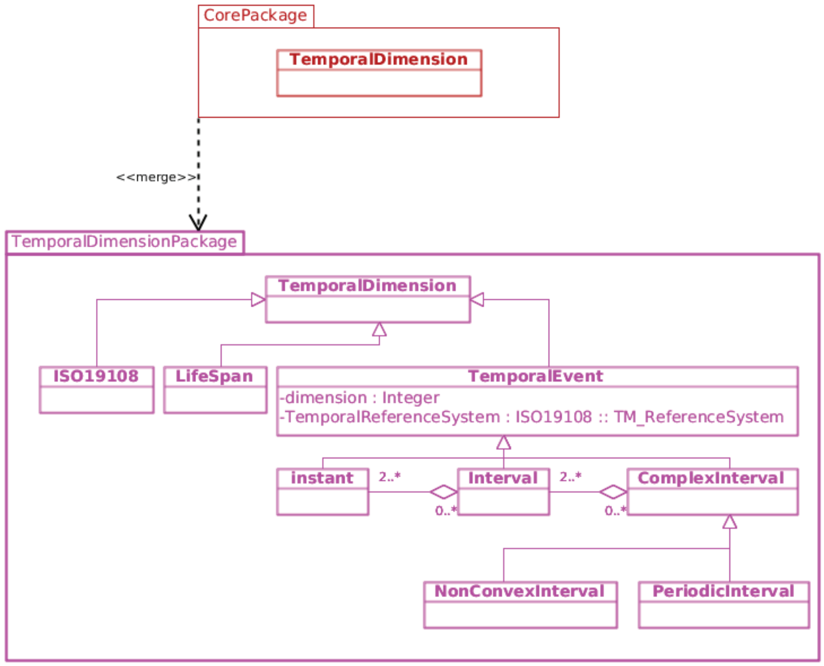

Figure 4: Temporal dimension package.

In the literature, there are two ways to describe temporality: talking about time, or modeling the change [8, 26, 27, 33, 38]. [26] argues that the temporal dimension is topologically similar to spatial dimension. Following this line of thinking, the ISO19108 standard [24] considers time as a dimension, by analogy to the spatial concepts defined in ISO19107. Based on this approach we define three classes, each one able to describe geographic features by the temporal dimension. The ISO19108 class allows the use of concepts that are defined in the standard, such as TM_Object. The LifeSpan class is dedicated to associate terminological information with a geographic feature, such as creation or evolution. The TemporalEvents class allows numerical information relative to a geographic feature to be represented. We use the TM_ReferenceSystem from ISO 19108 to specify the reference system corresponding to each event [24]. These events are defined by Instant (e.g., acquisition date of the image), Interval (e.g., from 2013/01/01 to 2013/02/28), or ComplexInterval, which is composed by a set of disjoint intervals. A ComplexInterval can be defined as PeriodicInterval (e.g., winter season from 2 past years) or NonConvexInterval (e.g., from 2012/11/01 to 2012/11/30 and from 2013/02/01 to 2013/02/28).

3.5 Semantic dimension

The aim of the SemanticDimensionPackage is to describe other characteristics of a feature, such those of image or landscape properties (Figure 5).

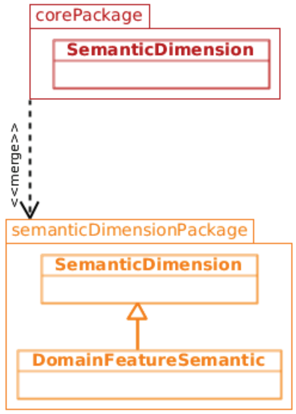

Figure 5: Semantic dimension package.

The SemanticDimensionPackage is defined by a set of concepts that are relevant for a domain of study, for example, the physical properties of an image (e.g., spectral band, texture) or the description of a landscape (e.g., Amazonian biome). This package serves to define explicitly the distinct properties of a feature in the different viewpoints (image and field) and thus, can only be specified when the application domain is known, in the model derived from the metamodel.

3.6 Relations

The RelationPackage contains all the required concepts for describing a relationship between features. It is directly linked to the CorePackage by the Relation association class. The Relation class is an abstract class that must be specialized into four sub-classes in order to refine the relationship in terms of spatial, temporal, spatiotemporal, and semantic relationships. Additionally, we provide three methods of definition to specify each type of relationship according to the viewpoint taken: (1) MeasurableMethod are methods that define relationships with numerical values (measured or calculated), such as those currently used in standards; (2) QualitativeMethod are methods used to define terms given by the expert to describe relationships; and (3) FuzzyMethod are instantiations of relations defined by the two previous methods on a $[0, 1]$ interval.

3.6.1 Spatial relations

The SpatialRelationPackage includes concepts to define spatial relationships between features (Figure 7), such as "near" or "50m away."

Researchers have taken many directions in order to define spatial relationships [10–12]. Their findings are currently used in the standards [24, 31]. We use the types defined in [9] to specify three classes of spatial relations: topological, projective, and metric. A MetricRelation includes distances or angles [14]. They can be defined by measurable methods (e.g., the town is located 5km away from the beach), qualitative methods (e.g., forest is near

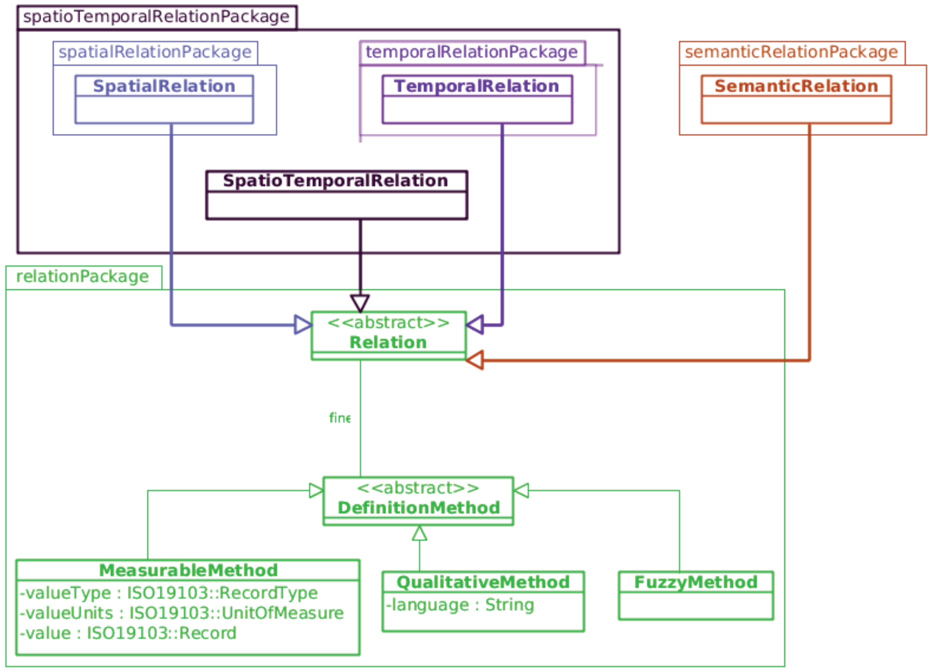

Figure 6: Relation package.

river), or fuzzy methods. A TopologicalRelation concerns connections between spatial objects. These relationships are generally defined by measurable methods (e.g., via the DE9IM matrix [12]), but can also be expressed by terminologically qualitative methods (e.g., "next to," "touches," "within"). Three approaches are regularly cited in the literature, namely: the point-set based nine intersection model by [12] (EhRelation); the logic-based region connection calculus model of [11] (RCC8Relation); or the calculus-based model of [10] (CBMRelation). We chose to define explicitly these three classes in our metamodel, because they are commonly used by several communities and they can be easily linked to one another [35]. A ProjectiveRelation is described by space projections, such as cardinal relationships (e.g., "east of," "north of") [14], or orientation relationships of the objects against each other (e.g., left, down, front) [21]. Different models have been defined to express these projective relationships between objects using different view of space [18, 28, 30, 32, 36]. A detailed description of these models can be found in [18]. Some of these models are best suited to describe projective relationships in the image point of view (e.g., the coarse direction relation matrix defined by [18], which is sensitive to the shape of the objects). These relationships are commonly defined with a reference frame in order to determine the direction in which the object is in relation with another object [37]. These reference frames are: *intrinsic*, which refers to the inherent object himself; *extrinsic*, which is defined by contextual factors (e.g., gravitation of the earth); and *deictic*, which is based on an observer's point of view. We chose to represent these reference frames by an attribute of the SpatialRelation class. This attribute's type is defined by another class which gives the name of the refer-

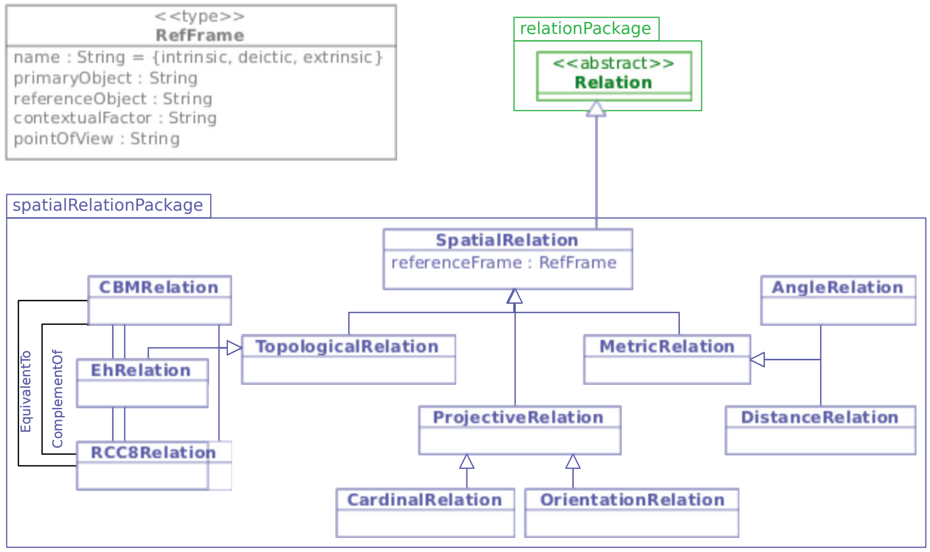

Figure 7: Spatial relation package.

ence frame (i.e., intrinsic, deictic, or extrinsic), and some necessary arguments (the primary object, the reference object, and/or the contextual factor (only for the extrinsic frame) and the point of view (only for the deictic frame).

3.6.2 Temporal relations

The TemporalRelationPackage includes concepts that define temporal relationships between features (Figure 8), such as "before" or "four months ago." As for the spatial relationships, we divide temporal relationships into three subclasses, namely: *metric*, *topological*, and *structural* TRelation classes. MetricTRelation deals with time measurement (e.g., the tide covered the mangrove three hours ago). TopologicalTRelation is concerned with temporal connections between temporal objects. Thirteen qualitative primitives have been defined by [1] to represent temporal relationships between intervals: *before*, *meets*, *overlaps*, *during*, *starts*, *finish*, their inverses, and finally the *equals* relationship. These relationships have been included in the ISO19108 standards [24] and are today increasingly used in temporal reasoning. Thus, we take these relationships into account in our metamodel. Finally, StructuralTRelation introduces the notion of parenthood between temporal objects (e.g., in terms of a timeline, the young mangrove is the parent of the adult one).

An important part in the understanding process of the phenomena is to have knowledge of the evolution of the studied object. However, these relationships can rely not only on features themselves, but also on their spatial dimensions (e.g., widening of a river bed during a flood) and/or semantic dimensions (e.g., evolution of cultural types in a registered land). Thus, as for spatial relationships, temporal relationships can be applied to all core classes.

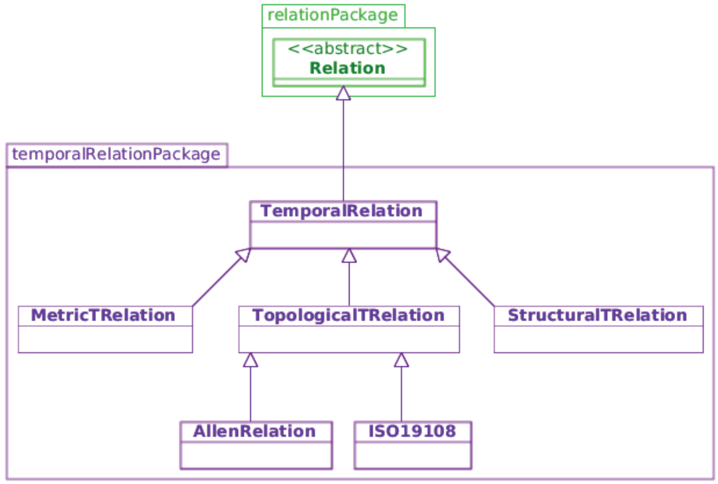

Figure 8: Temporal relation package.

3.6.3 Spatiotemporal relations

The SpatioTemporalRelationPackage includes concepts that define spatial and temporal relationships in order to describe the relationships between features located in space and time (Figure 9). Some recent research has already modeled spatiotemporal relationships [7, 19, 20]. [7] combines topological relationships between regions in a two-dimensional space defined by [12], with temporal relationships between convex intervals in time defined by [1]. These relationships are expressed by combining the name of the temporal relationship and the name of the topological relationship, such as (*finishes*, *touch*), (*equal*, *cover*), (*starts*, *overlap*). This approach results in a three-dimensional representation of relationships, well-suited to defining spatiotemporal relationships between independent and successive temporal regions. [20] supplements this work by proposing a set of relationships which is a generalized vision of existing spatiotemporal reasoning models. Based on this set, [19] has developed a model called *life and motion configurations*, which is used to formalize the relationships between two spatiotemporal histories. These configurations are generalized into a set of 25 relationships representing spatiotemporal information with a high level of abstraction. These can be expressed in natural language, such as "object A and object B meet during their coexistence," "A is there when B is born and dies," "A and B never meet," and so forth. In another way, [16] proposes a model that combines the RCC8 topological relationships with the Allen temporal relationships.

According to this previous work, we define a spatiotemporal relationship by a class composed with one or more temporal relationship *and* one or more spatial relationship, which have each been defined in the SpatialRelationPackage and the TemporalRelationPackage respectively. This approach is sufficient in our case to express the evolution of features in space and time, both in the field and image point of view. For example, we can express that during high tide the ocean covers the mangrove by the spatiotemporal relationship (*during*, *cover*) between the features mangrove and ocean.

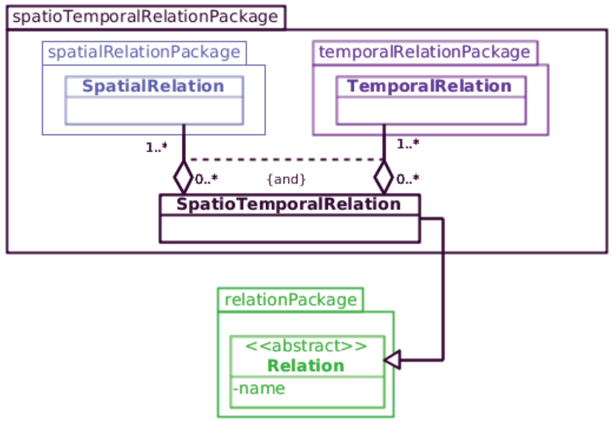

Figure 9: Spatiotemporal relation package.

3.6.4 Semantic relations

The SemanticRelationPackage includes all the others relationships that can exist between features, such as "part of" and "is a" relations (Figure 10).

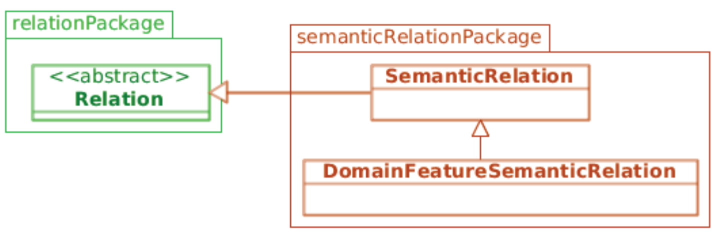

Figure 10: Semantic relation package

As for the semantic dimension, some of the most common semantic relations depend on the domain and cannot be explicitly specified in the metamodel (excepting *is a* and *part of* relations). The class of SemanticRelation therefore serves as an anchor to the package relationship that will only be used at the model level.

4 Experiments on the Amazonian littoral

We illustrate the relevance of our metamodel by applying it to satellite image interpretation. Our example concerns a calibrated (in reflectance and temperature) Landsat 5-TM image of the surroundings of the city of Santarem (in the Brazilian Amazon) from 07/12/2009 where we attempted to detect segments with different semantics (Figure 11). We obtained a so-called “good segmentation” [6] based on the preliminary semantic mapping of pixels of [4].

Figure 11: Landsat 5-TM calibrated image extract.

An application model was derived from this metamodel to express information about the Amazonian biome, according to the field and the image points of view. These models were then formalized into ontologies which are used to find littoral characteristics by reasoning (e.g., beach, mangrove, etc.)

4.1 Field point of view

We first focused our efforts on the description of the concepts relating to the domain of study.

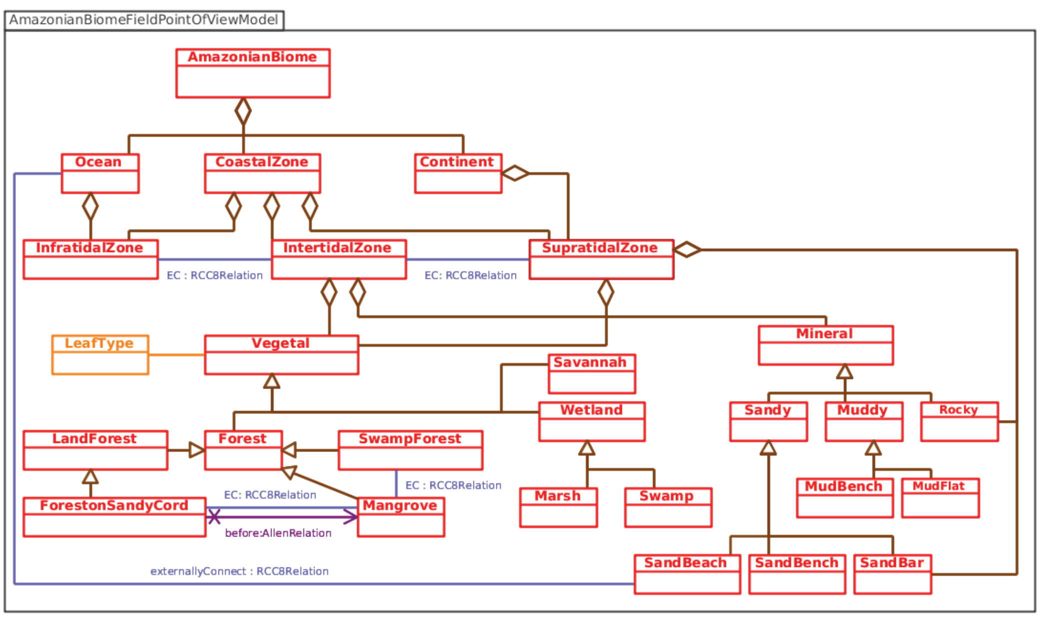

Figure 12: Field point-of-view model.

At this stage, we only use the two semantic relations, *is a* and *part of*, to describe aggregation and specialization relationships. For example, in this conceptualization, SandBeach (which is the focus of the study) is defined as a type of Sandy, which is also a Mineral. Then, the model was refined by adding spatial and temporal relations in accordance with the specifications given in the RelationPackage. Thus, to describe topological relationships, experts must take advantage of concepts defined in the metamodel. If the model is not adequate, experts may propose new terms. For example, to specify that a spatial relationship exists between the ocean and the beach, experts used the externally connected topological relation from the RCC8Relation class. Another example concerns the concept of Mangrove, which is defined as a type of Forest, and is also a Vegetal. Experts again used the externally connected topological relation from the RCC8Relation class to specify the relationship between the swamp forest and the mangrove. Finally, to express that the formation of forests on sandy cords (bars) is a thousand years older than that of mangrove, the expert uses the "before" temporal relation from AllenRelation class.

4.2 Image point of view

At the opposite of the field point of view, we also need to describe the representations of field entities in the image.

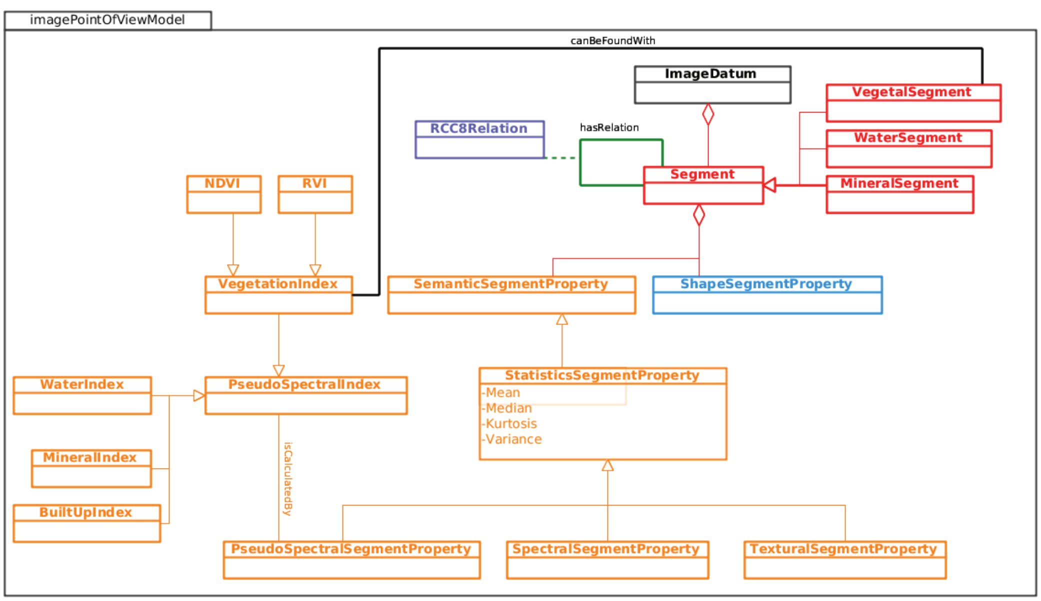

Figure 13: Image point-of-view model.

We achieve this by applying an object-based image analysis (using the Orfeo Toolbox software). On the one hand, the result of image computation is described using the *reference conceptualization* [13]. The reference conceptualization is formalized knowledge (an ontology) about basic concepts accepted by the community of a domain. Those concepts are relatively independent of any kind of application.

The reference conceptualization is also used to express expert concepts in *remote sensing contextual knowledge* [13]. This knowledge contains concepts depending on the context of the application. The expert knowledge is defined in terms of image characteristics (radiometric indexes, textures, shape etc.) We begin defining concepts of VegetalSegment, WaterSegment, and MineralSegment using radiometric characteristics (Figure 13).

4.3 Preliminary results

The image interpretations have been carried out by using ontologies, using description logic with TBox (terminological box) parts derived from the UML models presented above. The underlying logic rules allow us to achieve the segment classification automatically. The inference engine used for this task (FaCT++) is fed with the reference conceptualization (from the image profile), the contextual knowledge (from the field profile), and the image facts. The result of this ontological classification appears in Figure 14. This first classification allows different kinds of segments as water segments (in blue), mineral segments (in gray), and vegetated segment (in green) highlighted. Non-classified segments are represented in black.

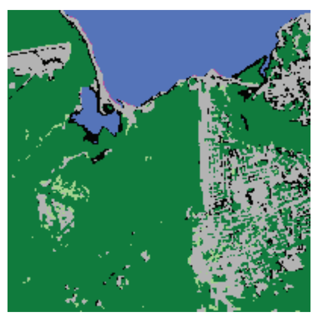

Figure 14: Semantic classification without spatial relations.

This ontological classification approach has been evaluated on classes defined without spatial relationships, comparing their retrieval to a commonly-used pixel threshold approach [2]. This approach ensures the formalized expert knowledge allows the classification of satellite images. Tables 1–3 show the results obtained for three different concepts on a 825×666 pixel Landsat 5 image of Santarem. The confusion matrices indicate the number of pixels classified in the same way (or not) using both methods. The overall accuracy (< 1) illustrates the rate of "well classified" pixels, and the kappa index ($-1 < \kappa < 1$) measures the agreement between both methods.

However, this interpretation is not sufficient if we want, for example, to classify other segments such as Beach or Mangrove. Indeed, to find these features, we must consider both image and field viewpoints, as well as the relationships between them, which are inherent in the definition of these features. Thus, this interpretation can be refined by taking topological and spatial relationships into account in the expert knowledge representation.

confusion matrix

threshold \ reasoning	non-vegetal	vegetal
non-vegetal	169727	3353
vegetal	4493	371877

Overall accuracy $= 0,986$

$\kappa = 0,967$

Table 1: Evaluation of ontological classification approach: confusion matrix comparing reasoning to threshold for vegetal semantics.

confusion matrix

threshold \ reasoning	non-mineral	mineral
non-mineral	512249	6439
mineral	8035	22727

Overall accuracy $= 0,974$

$\kappa = 0,745$

Table 2: Evaluation of ontological classification approach: confusion matrix comparing reasoning to threshold for mineral and built-up semantics.

4.4 Using spatial relations for reasoning

Some other expert concepts require spatial relationships to be defined. In this section, we focus on the classification of beach segments by using spatial relationships. Thus, we can define the Beach by the fact that it is a mineral-based land cover that is located between the ocean and the continent. The required spatial relation can be defined using RCC8, found in the SpatialRelationPackage. Indeed, in an image, we can distinguish the beach segment from the mineral one, by specifying that a BeachSegment is a MineralSegment externally connected to a WaterSegment. Beach segments thus described are automatically classified thanks to a description logic-based reasoner, which allows the extraction of semantics using reasoning based on spatial and topological relationships. Finally, this new classification allows segments of beach to be highlighted (colored in orange in Figure 15). In this figure, there are some mineral segments not adjacent to water ones that have been classified as beach segments. This is not a reasoning problem; instead it is caused by the implementation

confusion matrix

threshold \ reasoning	non-water	water
non-water	450572	249
water	287	98342

Overall accuracy $= 0,999$

$\kappa = 0,997$

Table 3: Evaluation of ontological classification approach: confusion matrix comparing reasoning to threshold for water semantics.

of the RCC8 relation *externally connected* in *Orfeo Toolbox* for raster images: this relation does not exactly map to the intuitive *adjacent* predicate.

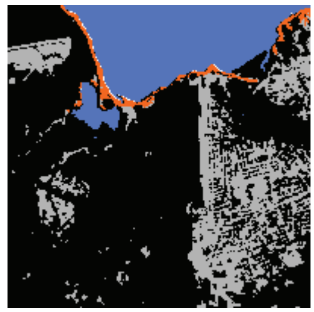

Figure 15: Semantic classification with spatial relations inference.

How can we validate this automatic interpretation result? Comparing it to expert interpretation one assumes the expert to be a reference. But which expert? There are many experts, each one producing an original interpretation giving his or her own expertise.

We asked two remote sensing experts to detect the river bank and produce thematic layers representing the beach. Then, we computed a common statistical analysis on the pixels (confusion matrix, overall accuracy, and κ index[1]).

(A) (B) (C)

Figure 16: Pixels retrieved for beach concept (in white) by reasoning (A) and by experts analysis (B and C).

Although the images appear very similar (Figure 16) and the overall accuracy is good, the κ index is not especially high (Table 4 and Table 5). So, what happened? This statistical artifact is most likely caused by the shape of the beach on the image, not easy to retrieve manually. Furthermore, the last expert's analysis has been saved in a shapefile. In order to produce confusion matrix comparing pixels to pixels, the raw expert data has been rasterized. All these approximations can cause loss of important pixels for this kind of narrow zone.

However, it is interesting to note that the comparison between two expert analysis is not always more concordant than the comparison between an expert analysis and our au-

[1]The κ index indicates the concordance between the compared results.

confusion matrix

threshold \ reasoning	non-beach	beach
non-beach	39089	187
beach	246	478

Overall accuracy $= 0,989$

$\kappa = 0,68$

Table 4: Evaluation of ontological detection of beach segments in comparison to expert B classification.

confusion matrix

threshold \ reasoning	non-beach	beach
non-beach	39163	341
beach	172	324

Overall accuracy $= 0,987$

$\kappa = 0,55$

Table 5: Evaluation of ontological detection of beach segments in comparison to expert C classification.

tomatic ontological analysis. Considering all the three analysis, it seems plausible that the automatic ontological result is comparable to human analysis.

5 Conclusions and perspectives

In this paper, we present a conceptual metamodel, based on normalized approaches, that can be used as a framework in the remote sensing domain to formalize spatiotemporal knowledge. Our aim is to support the interpretation of images by experts in various fields of research (e.g., ecology, health, and environment) and according to the associated point of view (e.g., field or image viewpoint). Thus, this metamodel was designed in a modular way, so that each package can be specified individually, facilitating the conceptual work of experts. Experts focus only on the formalization of their domain of expertise and integration becomes easier as a result.

For example, thematic experts use the metamodel to conceptualize the Amazonian biome in the field point of view. This first application has demonstrated the ease of use

confusion matrix

threshold \ reasoning	non-beach	beach
non-beach	39171	333
beach	105	391

Overall accuracy $= 0,989$

$\kappa = 0,64$

Table 6: Evaluation of expert B detection of beach segments in comparison to expert C classification.

of the metamodel to describe spatiotemporal knowledge from a particular viewpoint. We have also used this metamodel in the image point of view to conceptualize objects within the domain (e.g., beach segments) in a modular way. We then formalized all the knowledge in OWL ontologies and matched both viewpoints in order to define consistent links. Finally, we used description logic and reasoning to support image interpretation for the purpose of land cover classification.

In future work, we plan to use this metamodel in another context (e.g., health monitoring) in order to demonstrate its generality regardless of the domain of study. We also plan to use this metamodel in a context where the temporal dimension needs to be used to make interpretations. Future work on this metamodel will also aim to incorporate further temporal relationships, such as the relationship between disjoint intervals in order to treat more complex temporal situations (e.g., crop rotations monitoring by time series images). Finally, it will be necessary to model spatiotemporal dimensions in order to take into account dynamics of features more efficiently.

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