

Ontologies to interpret remote sensing images: why do we need them?

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The development of new sensors and easier access to remote sensing data are significantly transforming both the theory and practice of remote sensing. Although data-driven approaches based on innovative algorithms and enhanced computing capacities are gaining importance to process big Earth Observation data, the development of knowledge-driven approaches is still considered by the remote sensing community to be one of the most important directions of their research. In this context, the future of remote sensing science should be supported by knowledge representation techniques such as ontologies. However, ontology-based remote sensing applications still have difficulty capturing the attention of remote sensing experts. This is mainly because of the gap between remote sensing experts' expectations of ontologies and their real possible contribution to remote sensing. This paper provides insights to help reduce this gap. To this end, the conceptual limitations of the knowledge-driven approaches currently used in remote sensing science are clarified first. Then, the different modes of definition of geographic concepts, their duality, vagueness and ambiguity, and the sensory and semantic gaps are discussed in order to explain why ontologies can help address these limitations. In particular, this paper focuses on the capacity of ontologies to represent both symbolic and numeric knowledge, to reason based on cognitive semantics and to share knowledge on the interpretation of remote sensing images. Finally, a few recommendations are provided for remote sensing experts to comprehend the advantages of ontologies in interpreting satellite images.

Keywords: ontologies; remote sensing; knowledge-driven approach; geographic features; image interpretation; cognitive semantics; sensory gap; semantic gap

1. Introduction

Remote sensing science is evolving rapidly. The development of new sensors and easier access to the collected data are significantly transforming both the theory and practice of remote sensing. In this regard, two trends currently dominate. On the one hand, important research efforts are focused on data-driven techniques. In this regard, supervised classifiers such as Random Forest (Belgiu and Drăguț 2016) or Deep Learning classifiers (LeCun, Bengio, and Hinton 2015) led to promising results in terms of the accuracy of the created maps. These systems excel at perceptual classification (e.g. identify all pixels in an image that are similar to the annotated training samples) and are increasingly used in big data land cover applications relying on pixel-based statistical analysis of temporal dynamics on huge

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imagery datasets (Inglada et al. 2017; Hansen et al. 2013; Picoli et al. 2018; Souza and Azevedo 2017; Papadomanolaki et al. 2016). However, these approaches, by giving priority to inductive inference from data learning and neglecting cognitive approaches, are less efficient to deal with symbolic information (when abstractions are represented by symbols, e.g. forest – is made of – trees) (Marcus 2018). For example, an expert interested in mapping urban vegetation may collect training samples of “tree,” “grass,” “road” and “building” classes to run a supervised classification but, by doing so, s(h)e will not be able to map the “vegetation” class, unless s(h)e has previously (and manually) grouped together the samples of the “tree” and “grass” classes into a “vegetation” superclass. In addition, s(h)e will not be able to add spatial rules (i.e., similar to those in Ali et al., 2017) such as a “tree” cannot be located “inside” a “building,” but it can be located “inside” a “garden,” “park” or a “forest,” so that if a “tree” is “next to” or “surrounded by” a “building,” then it is located at a “garden.” This reasoning limitation is a problem because most end-users of Earth Observation applications (e.g. geographers, ecologists, agronomists, etc.) are used to work with symbolic definitions. For instance, the Land Cover Classification System (LCCS) proposed by the FAO is entirely based on inference rules. For example, a land cover class is defined by specific rules applied on properties such as vegetation cover, vegetation height, leaf type, phenology, etc. As a consequence, these “black box solutions” (Zhu et al. 2017) do not match with the way end-users are used to conceptualize their research subject and they may thus deepen the gap between image processing scientists and end-users.

On the other hand, whereas the expert knowledge mobilized by environmental scientists to interpret remote sensing images tends to be somehow discarded from the data-driven image analysis, the development of knowledge-driven approaches has been identified as one of the most important directions of research by the remote sensing community (Chen et al. 2016). In this regard, Geographic Object-Based Image Analysis (GEOBIA) is a significant trend in remote sensing which makes it possible to classify image objects (e.g. groups of pixels sharing common properties) in satellite images based on image analysis procedures that rely on a priori expert knowledge (Blaschke 2010; Belgiu, Dragut, and Strobl 2014; Baltsavias 2004). GEOBIA is now considered as a new paradigm in remote sensing (Blaschke et al. 2014) since it accounts for complex spatial topological and non-topological relationships, shape and texture information, leading to better results than pixel-based approaches (Weih and Riggan 2010). However, it approximates to a certain degree the computer-aided photo-interpretation which has been criticized for being highly subjective (Belgiu, Dragut, and Strobl 2014). As a result, GEOBIA rule sets correspond to image processing chains that are rarely transferable and thus appear ill-suited to address the challenges of the era of big data (Arvor et al. 2013).

Considering recent advances in big data image processing based on data-driven approaches and the new paradigm of knowledge-driven image analysis, we consider that hybrid approaches combining inductive and deductive processing methods would be the best way to fully exploit the capacity of remote sensing applications. In this context, better handling of expert knowledge used to process remote sensing images should be a priority when implementing hybrid methods. Whereas important efforts are carried out to share products derived from satellite observations including global and regional land cover maps (Grekousis, Mountrakis, and Kavouras 2015; Congalton et al. 2014a), to share calibration and validation data (See, Fritz, and McCallum 2014) or to share methods (e.g. algorithms implemented on Google Earth Engine, R and Python libraries for image processing, GEOBIA rulesets shared online) within the scientific community, little effort is dedicated to formalizing, aggregating and sharing expert knowledge in remote sensing. In this context,

knowledge representation techniques like ontologies represent a great potential to address this problem and to advance remote sensing science (Arvor et al. 2013).

In philosophy, ontology is the study of the kinds of things that exist (Chandrasekaran, Josephson, and Benjamins 1999, Couclelis 2017). However, in our study, we are more concerned with the Artificial Intelligence definition of the term ontology. An ontology is usually defined as “a *formal, explicit specification of a shared conceptualization*” (Gruber 1995) providing a non-ambiguous and formal representation of a domain. A conceptualization is an abstract, simplified view of the world with a specific purpose. The definition thus rests on two pillars: (1) “explicit” means that all concepts and relations are explicitly formalized and (2) “shared” means that the ontology represents consensual knowledge in a specific domain, i.e. it has been approved by a scientific community. Formal ontologies should provide a common vocabulary and meaning to allow computer applications to communicate with each other (Guarino, 1998) and also to communicate with users. Formal ontologies are based on description logics (DL) that allow reasoning and inferring new knowledge.

Thus, ontologies are formal ways to explicitly specify domain knowledge, by defining the properties of the concepts of interest and the relationships that hold them together (e.g. “a tree – is a kind of – vegetation,” “a leaf – is part of – a tree,” “the beach – is adjacent to – the sea,” “a park – has – trees – and – playgrounds,” “a garden – belongs to – a building,” “a forest – has more – trees – than – a garden,” etc).

The main advantages offered by an ontology for remote sensing applications (Ontology-RSA, for short) based on description logics are the following:

- (1) Symbol Grounding. The association of the right concept with the right sensing data (a.k.a. symbol grounding) and the association between concepts themselves. DL-ontologies represent a formalism for providing high-level representations of low-level data (e.g. remote sensing image analysis).
- (2) Knowledge sharing. The use of a common conceptualization (vocabulary and semantics) and the adoption of a standard ontology language provides a mechanism for publishing representations of remote sensing images so that they can be shared and reused among intelligent agents.
- (3) Reasoning. The adoption of a description logics ontology representation allows the use of description logics reasoners that can infer new knowledge from explicit descriptions. This gives some freedom and flexibility when inserting new facts (e.g. new remote sensing image descriptions), because new knowledge can be automatically classified.

Formal ontologies have long been successfully used in various scientific domains such as genetics (Ashburner et al. 2000), ecology (Madin et al. 2008, 2007), eco-informatics (Williams, Martinez, and Golbeck 2006) and biology (Bard and Rhee 2004). However, their use in geography remains limited to applications in Geographical Information Systems (GIS) (Agarwal 2005; Kavouras and Kokla 2002), i.e. OSM ontology by Codescu et al (2011). In this case, formal ontologies are used to mediate between heterogeneous systems and data sources (Fonseca et al. 2002), to add semantic annotations to geo-databases (Lüscher, Weibel, and Burghardt 2009), to improve spatial data discovery (Lutz and Klien 2006) and knowledge sharing among user communities (Stock et al. 2013), and to interpret spatio-temporal changes in cadastral data (Stock et al. 2015), administrative units (Gantner et al. 2013) or in historical places (Hyvönen et al. 2011). In addition, ontologies were also successfully used in remote

sensing (Arvor et al. 2013) and specialized workshops held at international remote sensing conferences (e.g. GEOBIA 2014, 5th GEOBIA Conference, Thessaloniki, Greece, 21-24 May, 2014). Ontologies have then been used for semantic annotation of satellite images using domain ontologies (Amiri, Farah, and Farah 2017), to validate remote sensing workflows (Liu et al. (2017), to structure and describe processing chains in remote sensing (Nys et al. 2018) or to improve the discovery and selection of satellite sensors depending on expected applications (Hu et al. 2018). A major application consists in using ontologies to interpret remote sensing images. In this regard, ontologies have been used for explicit representation of features to be extracted from satellite images (Nasri, Nefzi, and Farah 2018; Moran et al. 2017) for automatic urban feature recognition from LiDAR data (Xing, Mostafavi, and Chavoshi 2018), for individual buildings extraction from TerraSAR-X images (Gui et al. 2016), for analyzing very high resolution SAR images (Espinoza-Molina et al. 2015), for coastal area mapping from multi-spectral imagery (Huang et al. 2017), for pixel-based classification based on spectral rules (Andrés et al. 2017), for spatio-temporal knowledge modeling (Pierkot et al. 2013). Finally, a few papers have also especially been published about ontologies and GEOBIA (Pierkot et al. 2013; Belgiu et al. 2014; Espinoza-Molina et al. 2015; Gu et al. 2017; Andrés et al. 2017; Rajbhandari et al. 2017).

Despite the growing interest in Ontology-RSA, ontology designers still have difficulty getting the attention of remote sensing experts (Chen et al. 2018). This difficulty may be due to the gap between the remote sensing experts' expectations of formal ontologies (still often considered as a buzzword) and their real possible contribution to remote sensing. This gap may be due to the fact that ontology specialists often succeed in implementing technically an ontology-based image classification, but fail to justify why they chose to use formal ontologies for their remote sensing application instead of a more traditional approach. The primary objective of this paper is to reduce this gap. To this end, this paper provides:

- highly necessary clarifications concerning the conceptual limitations of the current knowledge-driven approaches in remote sensing (Section 2),
- explanations about why formal ontologies can help (at least partially) overcome these limitations (Section 3),
- a discussion about important research directions for ontology designers interested in remote sensing applications (Section 4); and,
- answers to questions often raised by remote sensing experts when trying to comprehend the advantages of using formal ontologies to interpret satellite images (Section 5).

The goal of this paper is thus neither to conduct an exhaustive review of existing work dedicated to Ontology-RSA nor to provide additional ontology-based classifications, i.e. experimental research. The goal of this paper is to explain how ontologies can enhance the interpretation of remote sensing images.

2. The difficult formalization of expert knowledge

The interpretation of satellite images is a complex task, from the selection of the relevant data for a given application (Phinn 1998; Phinn et al. 2000) to the image content analysis, which is closely interrelated with the data characteristics (mainly spectral, spatial, radiometric and temporal resolutions; Jensen 1983) and the users' skills (Belgiu, Dragut, and Strobl 2014). Whereas data-driven approaches have long been implemented, knowledge-driven approaches

(especially GEOBIA) gained importance in the last decade with the aim of reducing the gap between the data and the end-users' needs. In this regard, users attempt to identify classes of interest in images by setting classification rules based on their expert knowledge.

To illustrate this point, this paper intentionally presents an overly simple example based on the class "forest" in order to focus our comments on the conceptual issues related to the approach, instead of deflecting attention to the relevance of the image processing rules. It is worth mentioning that this example can be adapted to any other class of interest (crops, buildings, water bodies, etc) since all the limitations mentioned in this section are valid for any class. Our practical example concerns the mapping of forests in Mato Grosso region of the Brazilian Amazon using a single date multispectral remote sensing image (e.g. a Sentinel 2 image) acquired during the dry season (e.g. July, 26th, 2017). In order to map this land cover class, one might assert that (1) Amazon forests are characterized by high aboveground net primary productivity (NPP) and (2) the normalized difference vegetation index (NDVI) is a satellite-based vegetation index tightly correlated with aboveground net primary productivity (Pettorelli et al. 2005). Remote sensing experts might thus compute an NDVI image to highlight the presence of vegetation, thereby enabling better identification of "forest" areas. These experts then need to convert their visual perception of "forest" areas in an NDVI image into a classification rule set. For example, after a trial and error analysis, the users might decide that the "forest" class should be assigned to pixels (or image objects) with high NDVI values. In that case, let us define a "high NDVI" value as a value greater than a threshold of 0.6 such that the classification rule is $\text{Forest} = (\text{NDVI} > 0.6)$. An example of such classification is introduced in Figure 1.

To summarize, as shown in Figure 2, the knowledge-driven approach consists in translating "human perceptual knowledge" (i.e. the visual mechanism that enables a user to identify a class of interest in a remote sensing image) driven by "symbolic knowledge" (i.e. expert knowledge about the class of interest and remote sensing image processing makes him to define that "Forest has high NDVI values") into "numeric knowledge" (i.e. the implementation of a classification rule set: $\text{Forest} = (\text{NDVI} > 0.6)$). Once the rule has been defined, experts still have to adapt their perceptual knowledge to the computational system (e.g. to implement the rule set in a remote sensing software, such as eCognition as in Figure 2, bottom left) in order to translate their symbolic knowledge into a numerical value the application can interpret. It is worth noting that, in the "traditional" remote sensing, the symbolic knowledge is usually implicit (Figure 2) since the users generally implement directly the rules based on trial and error tests without formalizing their knowledge about the relationship between NDVI and NPP. Therefore, the remote sensing experts make use of an ontology when extracting information from remote sensing data. However, the used ontology is not made explicit.

The entire process to convert "perceptual knowledge" into "numeric knowledge" raises important issues that need to be discussed in order to understand the conceptual limitations of knowledge-driven approaches. These issues refer to the complexity of defining geographic classes (Section 2.1), their concept duality (real-world entity vs. image object, Section 2.2), their vague and ambiguous definitions (Section 2.3) and the sensory and semantic gaps (Sections 2.4 and 2.5) (Figure 3).

2.1. The complex definition of geographic concepts

The first issue concerns the definition of the classes of interest. Indeed, geographic concepts can have many definitions (Bennett 2002) depending on the physical, historical, functional or conventional mode of definition used (Bennett 2005) (Figure 3, 1 – Modes of definitions).

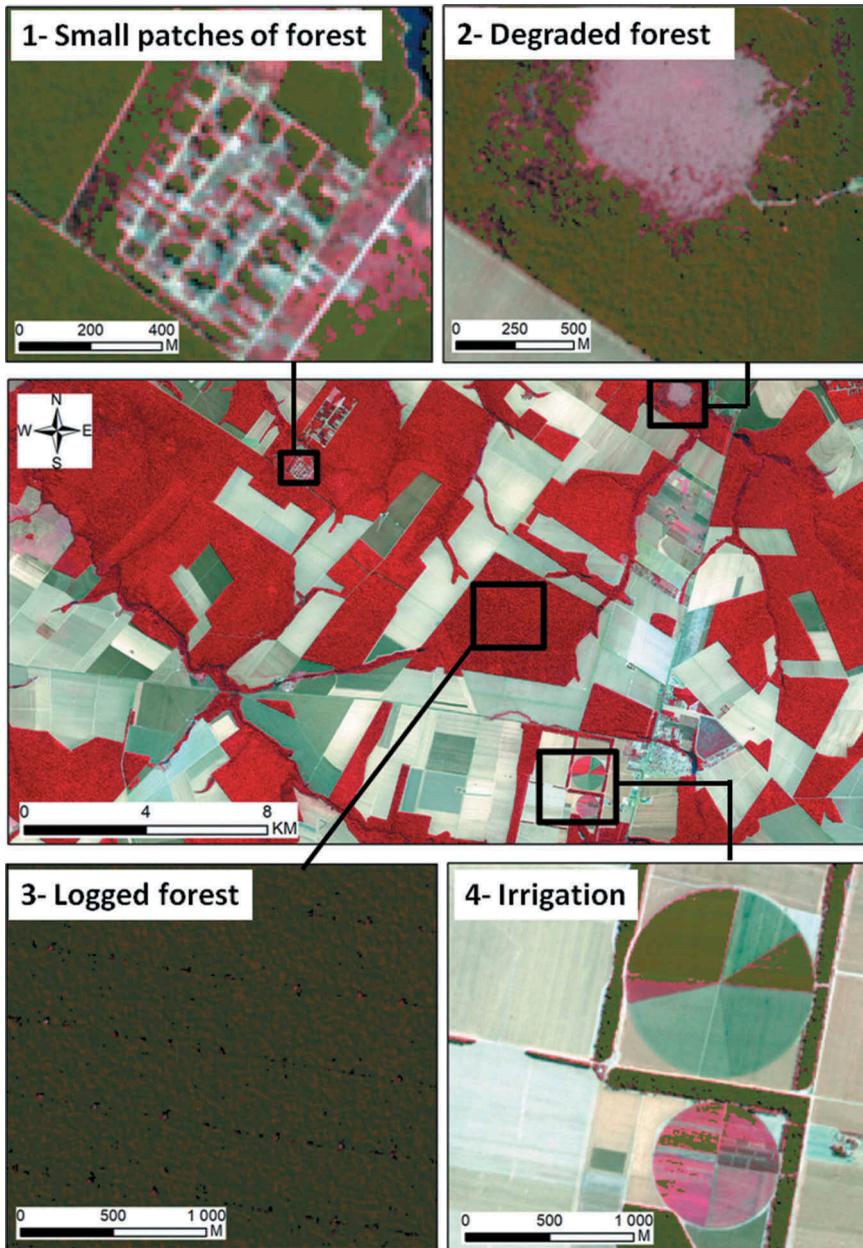


Figure 1. False color composite of a Sentinel-2 image of a region in the Brazilian state of Mato Grosso (07/26/2017). In boxes, forest areas are shown in green and identified by applying the classification rule: Forest = (NDVI > 0.6). These boxes illustrate the issues related to vagueness (boxes 1 and 2), partiality (boxes 2 and 4) and ambiguity (boxes 2 and 3) of the forest class. In box 1, pixels are classified as forest although they constitute patches that are too small to be considered as forests. In box 2, only some pixels of a degraded forest are classified as forest although the entire area may be considered as degraded. In box 3, some pixels inside a logged forest are not classified as forest although they may be considered as part of the forested area. In box 4, irrigated crops are misclassified as forests, so that the classification rule appears to be a partial description of the forest concept. The colour version of this figure is available on the on-line journal paper.

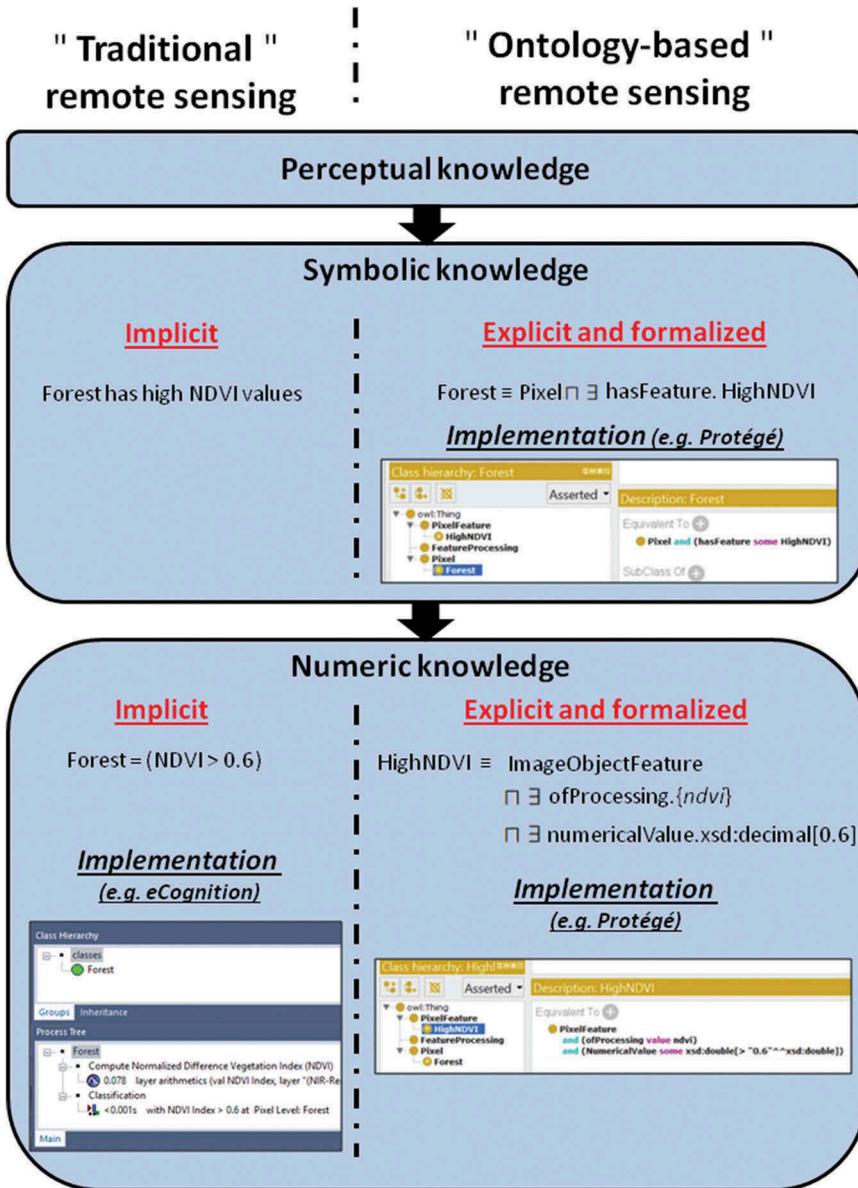


Figure 2. Implementation of a classification rule in knowledge-driven remote sensing using a “traditional” and an “ontology-based” approach. In “traditional” remote sensing, the perceptual knowledge is implicitly converted into symbolic and numeric knowledge and finally implemented in a remote sensing software (e.g. eCognition). In “ontology-based” remote sensing, both the symbolic and numeric knowledge are explicitly formalized based on Description Logics. They are then implemented in ontology editors such as Protégé. In Description Logics, the symbol \equiv stands for equivalence, the symbol \exists stands for existential quantifier and can be interpreted as “there exists” and the symbol \cap stands for intersection. In this example, the conceptual framework to model the classification rule is inspired from Andrés et al. (2017) and can thus be interpreted as follows. At symbolic level, a “Forest” is defined as a pixel that has a characteristic (*hasFeature*) which is “HighNDVI.” The concept of “HighNDVI” is then defined as a “PixelFeature” resulting from a processing (*ofProcessing*) named “ndvi” (“ndvi” being an instance of a “FeatureProcessing” concept) and whose numerical value is greater than 0.6. The colour version of this figure is available on the on-line journal paper.

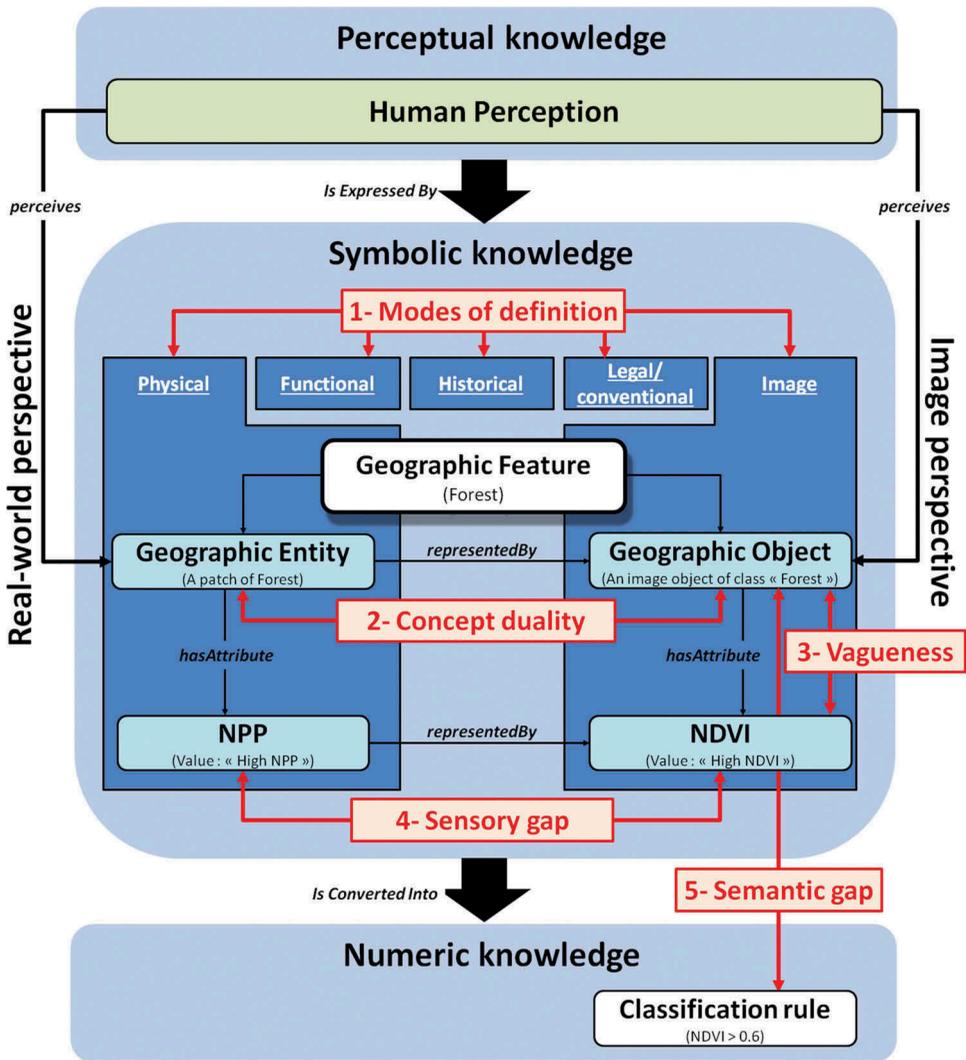


Figure 3. Schema followed to formalize expert knowledge, according to the real-world and the image perspective. In both cases, the human perceptual knowledge is expressed by a symbolic knowledge (e.g. a “Forest” is a geographic entity with a “high NPP” or “Forest” is a geographic object with a “high NDVI” value). In the image perspective, the symbolic knowledge is then converted into a numeric knowledge (e.g. Forest = (NDVI > 0.7)). In that case, it is worth noting that the symbolic knowledge is actually often implicit since remote sensing experts directly convert their perceptual knowledge into classification rules. The five conceptual issues are then identified in red. The colour version of this figure is available on the on-line journal paper.

These modes represent alternative points of view of the classification of objects, i.e. a concept can be defined by alternative definitions that are not strictly equivalent, although they are naturally correlated (Bennett 2010). For example, a forest can be described from a functional viewpoint in which the main interest is the role of forests in storing carbon, by considering the NPP like in the example described above. However, a forest can also be described based on its historical properties in order to consider only primary forests.

Furthermore, the interest may only be in mapping forests in the Legal Amazon, in which case forest patches outside the limits of the Legal Amazon as delimited in 1953 will be discarded. Finally, and maybe most importantly for remote sensing applications, a forest can be defined based on its physical description. In this regard, major efforts are required to standardize the description of land cover classes (e.g. the Land Cover Classification System (LCCS); Di Gregorio 2005). Various organizations and countries now have their own definition of a “forest” (Chazdon et al. 2016). For example, in Brazil, a “forest” is defined as “an area greater than 1 hectare, with more than 30 percent canopy cover and a minimum tree height of 5 meters.” In China, a forest is a piece of “land with a minimum area of 0.67 ha, minimum 20% crown cover and a minimum tree height of 2 meters.” As a consequence, when a remote sensing expert sets a classification rule such as Forest = (NDVI > 0.6), the definition of the “forest” concept is implicit and leads to information (e.g. a map of forest areas) that has to be interpreted with caution by end-users or remote sensing colleagues.

2.2. *The concept duality of geographic concepts*

In addition to these definitions, a remote sensing expert has to deal with the image perspective. Strahler, Woodcock, and Smith (1986) distinguish “between the *scene*, which is real and exists on the ground, and the image, which is a collection of spatially arranged measurements drawn from the scene.” The elements measured in an image are then considered as abstractions of real objects in the ground scene (Woodcock and Strahler 1987). More concretely, the “forest” concept can be defined both from the real-world perspective, based on its physical properties (e.g. “a forest has high NPP values”) and from the image perspective, based on its image properties (e.g. “a forest has high NDVI values”). The real-world and image definitions of the same abstract concept are hereafter referred to as concept duality (Figure 3, 2 – Concept duality). In our example, “forest” is the abstract concept, also named a geographic feature since a feature is “an abstraction of a real-world phenomenon” (ISO19101 ISO19101 2014). A geographic feature is then considered as a superclass including both sub-concepts of a geographic entity and a geographic object (Mark 1993). A geographic entity is a real-world entity characterized by attributes (e.g. NPP, leaf type, phenology, tree height, etc.) which are assigned attribute values (e.g. 2000 g/m²/year, broadleaved, evergreen, 15 meters, etc.) and that occupies a position in space (e.g. a patch of forest) (Mark 1993). The representation of a geographic entity in an image is called a geographic object where an object is a “thing” in the digital world, which represents real-world phenomena as an instance of a generally recognized category (Voudouris 2010). This geographic object is also characterized by attributes (e.g. NDVI) and its corresponding values (e.g. 0.8). Finally, it is worth noting that the observation of a geographic feature in a remote sensing image depends on the choice of an appropriate scale of analysis, or spatial resolution, for a given application (Woodcock and Strahler 1987).

2.3. *The vagueness and ambiguity of geographic concepts*

Beyond the variety of definitions of geographic concepts, linking attributes (e.g. NDVI) and corresponding values (e.g. “high”) to geographic concepts (e.g. “forest”) is not a simple task because the latter are often vague and ambiguous (Figure 3, 3- Vagueness). Also, note that different kinds of vagueness and ambiguity can coexist (Bennett 2005). Firstly, threshold vagueness arises when qualitative terms (e.g. “high”) are used to distinguish objects that in

fact exhibit continuous variation in the observables (e.g. NPP or NDVI). Asserting that “high NDVI” (or “high NPP”) values represent forests is thus vague since it requires setting a user- and context-dependent threshold in a continuous gradient of vegetation (Figure 1, boxes 1 and 2). Secondly, partiality refers to the fact that “high NDVI” is a partial description of the “forest” concept in remote sensing images since it does not make it possible to either (1) map only forests (other classes such as “crops” may also have high NDVI values; Figure 1, box 4), or (2) to map all the different types of forests (some “degraded forests” for example may have lower NDVI values; Figure 1, box 2).

Ambiguities cover all cases in which natural language expressions can have more than one meaning (Unger and Cimiano 2011). The most common ambiguity is lexical ambiguity, which “arises due to homonymy of a natural language expression, i.e. an expression that has several lexical meanings, where each of these meanings can be mapped to one ontology concept unambiguously” (Unger and Cimiano 2011). For example, Lund (2006) gathered more than 800 definitions of the “forest” concept across the world, each of them being explicitly defined when considered separately. In addition, deep ambiguity (or open texture) may also exist when “a term has no crisp boundaries and may shift its meaning over time as new technologies appear, as people develop new habits, and in general, as the social and physical context of the term evolves” (Wieringa 2003). For instance, Chazdon et al. (2016) consider that commonly used definitions of forest have limited utility for assessing and monitoring new and diverse forms of forest cover such as “reforestation,” “degraded forest” or “logged forest” (Figure 1, boxes 2 and 3). In this regard, it is worth noting that vagueness differs from ambiguity: whereas threshold vagueness can be reduced by defining more precise rules, deep ambiguity cannot (Shapiro 2006).

2.4. The sensory gap

The sensory gap derives directly from the dual definition of abstract geographic features (Figure 3, 4 – Sensory gap). It is defined as the gap between the entity in the world and the information in a (computational) description derived from a recording of that scene (Smeulders et al. 2000). Whereas remote sensors can measure fundamental biophysical variables, few domain experts (e.g. in ecology or geography) are actually aware of what is really measured by remote sensing because basic research on these issues is conducted and published in other disciplines (Jensen 1983). For example, in our case, experts asserted that the NDVI is an appropriate index to map forests because it is correlated with NPP. However, NDVI is not a measure of NPP. And NPP cannot be reliably measured from a single date optical multi-spectral image because it does not provide information on vegetation height, for instance. In this regard, the sensory gap is an ill-posed problem that yields uncertainty in the description of geographic objects (Smeulders et al. 2000).

The sensory gap issue is even exacerbated when the objective is to map a nominal scale “hybrid” variable such as land cover (e.g. “forest”) since a “hybrid” variable is created by systematically analyzing more than one fundamental biophysical variable (Jensen 1983), thus cumulating uncertainties. This assertion is valid even when the description of the “hybrid” variable is made explicit, through the “Broadleaved Evergreen High Trees” class from the Land Cover Classification System (LCCS; Di Gregorio 2005) instead of “forest,” for instance. A single date optical remote sensing image only captures a partial representation of this definition, without explicit information on vegetation height, leaf type, and phenology. As a consequence, Congalton et al.

(2014b) emphasize that land cover products are often based on classification schemes (such as LCCS) that are defined from an ecological or environmental perspective and include some land cover classes that in fact cannot be identified from optical remotely sensed imagery.

2.5. *The semantic gap*

The semantic gap is closely linked to the vagueness and ambiguity of the geographic concepts. The semantic gap is the lack of agreement between the information that one can extract from the visual data and the interpretation made of the same data by a user in a given situation (Smeulders et al. 2000). It describes the gap between the low-level representation of an image (e.g. NDVI values assigned to pixels) and the high-level semantic concepts used by users to interpret the image (e.g. forest) (Smeulders et al. 2000) (Figure 3, 5- Semantic gap). The main explanation for this gap is that humans trigger perceptual mechanisms (i.e. “perceptual knowledge”) to draw inferences from what they perceive in remote sensing images (Biederman 1987). These mechanisms of human observation cannot be easily translated into computational representation, i.e. into “numeric knowledge” e.g. Forest = (NDVI > 0.7). The translation first requires expressing the perception in symbolic concepts (Bachimont, Troncy, and Isaac 2002), i.e. as “symbolic knowledge” (e.g. “Forest has high NDVI values”), which is a complex task, since not all percepts can be easily expressed with natural language. This is especially true for properties, named *sense qualia*, which are not measured by humans when describing geographic objects and entities (Coculelis 2010). For example, although *color* may be considered as a fundamental biophysical variable related to the spectral signature (Jensen 1983), it is also a typical *sense qualia* since its perception varies amongst humans and is difficult to express (see the list of color names defined in the R programming software: “antique white,” “hot pink,” “royal blue,” “gray0” to “gray100”). In our example, “high NDVI” may be associated with a color that is subjective and meaningless for most people, except for remote sensing experts.

3. **Ontologies to formalize, represent and share remote sensing knowledge**

Based on the above-mentioned considerations, it appears that remote sensing experts are mainly used to working with numeric knowledge from an image viewpoint (e.g. Forest = (NDVI > 0.7)). This approach implies that experts use partial and implicit representations of their expert knowledge, which is then difficult to share with other scientists (e.g. in ecology, agronomy, urban studies, geo-health, etc.) who are used to working with symbolic knowledge and real-world concepts (e.g. in ecology, a forest might be defined by concepts such as broadleaved, evergreen or trees and does not need to be linked to image features). In this context, formal ontologies are an especially promising way to enhance remote sensing science since they make it possible to represent both symbolic and numeric knowledge about both real-world and image viewpoints.

3.1. *A brief definition of ontologies*

As aforementioned in the Introduction section, an ontology is first designed to represent knowledge about a domain of interest. Ontologies can be implemented according to standard formalisms such as the Web Ontology Language (OWL). OWL is a W3C (World Wide Web Consortium) standard related to description logics (DLs) (Baader

2003), which is a valuable support for the semantic web as the concept and role hierarchies fit the context of the web particularly well. In DLs, a given subject area is described in terms of (1) concepts (or classes) organized in a hierarchy of concepts (e.g. “Forest” is a sub-class of “Vegetation”), (2) roles (or properties) organized in a hierarchy of roles (e.g. “is Adjacent To” is a sub-role of “has Spatial Relation”) and (3) individuals (or objects) (e.g. an image object classified as forest is an instance of the Forest concept).

Figure 2 introduces a concrete example of the implementation of an Ontology-RSA considering the classification rule used in this study. Note that, different from “traditional” remote sensing, both the symbolic knowledge and numeric knowledge are explicitly formalized based on DLs so that they can then be implemented in an ontology editor (e.g. Protégé). Based on OWL and DLs formalisms, the reasoner algorithms then enable new implicit knowledge to be inferred (e.g. to assign individual pixels to higher level geographic features as in Andrés et al. 2017) or to check for inconsistencies (Bannour and Hudelot 2011) (e.g. estimating vegetation height based on multispectral images may not be reliable).

3.2. *Ontologies as ways of explicitly specifying bodies of knowledge*

The formalization of concepts and relations expressed in ontologies is a key to addressing the major issues listed in Section 2. Formal ontologies can be used to explicitly describe an observation (e.g. of a forest) from different perspectives. As an example, the Extensible Observation Ontology (OBOE; Madin et al. 2007, 2008) was specially designed to describe the semantics of scientific observations. In OBOE, an observation of an entity (e.g. a tree) is made through the measurement of a characteristic of this entity (e.g. biomass) based on a measurement standard (e.g. gram). A similar approach can also be used to describe geographic features: a forested area can be described thanks to one characteristic (e.g. NPP) and its associated value (e.g. “HighNPP”). In that case, the description corresponds to the functional definition of a forest (see Section 2.1), but other characteristics can be included in order to consider other modes of definition (Figure 4). Measurements of vegetation cover (in %), vegetation type (e.g. trees or shrubs), leaf type (broadleaf or needle), phenology (evergreen or deciduous), vegetation age (in years) may complete the description of a forest using physical and/or historical modes of definition. Further, the observation of an entity (e.g. forest) can be associated with a context to enable the description of the relationships between the entity and other entities at the time of the observation (e.g. the entity of forest is located within the Amazon basin).

Ontologies also allow perspectivalism, that is, separating the field point of view used to describe the properties of the feature in the field reality (e.g., high NPP, leaf type, etc.) and the image point of view used to describe the characteristics of the object in the image (e.g., high NDVI, texture, wavelength, etc.). This approach takes into account the concept duality of geographic features (including both geographic entities and geographic objects) and improves the semantic interpretation of satellite images (Pierkot et al. 2013) (Figure 5). A geographic feature is thus described based on its image characteristics as in Andrés et al. (2017), who classified the pixels in Landsat images based on spectral rules. In this case, a pixel (or image object) of a given class (e.g. Forest) is described by an image feature (e.g. NDVI) and its associated value (“HighNDVI”) that results from the application of an image processing task (e.g. applying a threshold on an NDVI image). The formalization of the “HighNDVI” concept makes it possible to clarify the relationship between symbolic (e.g. “HighNDVI”) and

numeric knowledge (e.g. $\text{NDVI} > 0.7$) thereby reducing the semantic gap. Similarly, the description of both real-world geographic entities and their corresponding geographic objects facilitates connections between concepts from both perspectives (for example, between NDVI and NPP), thus reducing the sensory gap (or at least making it explicit) (Figure 4).

The explicit formalization of geographic features is also a good way to address the problem of ambiguity. For example, lexically ambiguous concepts can be described by different definitions (e.g. the 800 definitions of the forest concept; Lund 2006). To handle formal ontologies including such ambiguous concepts is a difficult task, especially when performing queries. In this regard, underspecification approaches (i.e. reduction of the information/properties used to describe a concept) have been proven to limit misinterpretations (Unger and Cimiano 2011; Reyle 1993). However, it is worth noting that formal ontologies do not solve the deep ambiguity issue (e.g. to consider a reforested area as a forest is still ambiguous) but at least forces the experts to clarify how they define the concepts used in a given application (e.g. the difference between a forested and a reforested area has to be explicitly defined).

Ontologies can also help to address vagueness issues, i.e. threshold vagueness and partiality. On the one hand, fuzzy ontologies can be used to address threshold uncertainty, since concepts are defined as sets with vague definitions. Qualitative measures like green area, round lake, etc. are given a degree of truth to indicate the degree of greenish, roundness, etc. (Bobillo and Straccia 2011). Similarly, probabilistic ontologies define concepts using probabilistic sets, in which the values of the set properties have probabilities attached, and statistical measures are computed to determine the probability of an individual being a member of a concept, given the probabilities of the property values. Probabilistic ontologies allow uncertainty in membership, but the concepts themselves are clearly defined (Costa and Laskey 2006). Other ontologies use heuristics to determine if a given instance is a member of the concept defined by the heuristics in a data-driven manner (rather than axioms as in a classical ontology). Heuristic ontologies do not use logical inference, but rather statistical approaches, i.e. optimization algorithms based on

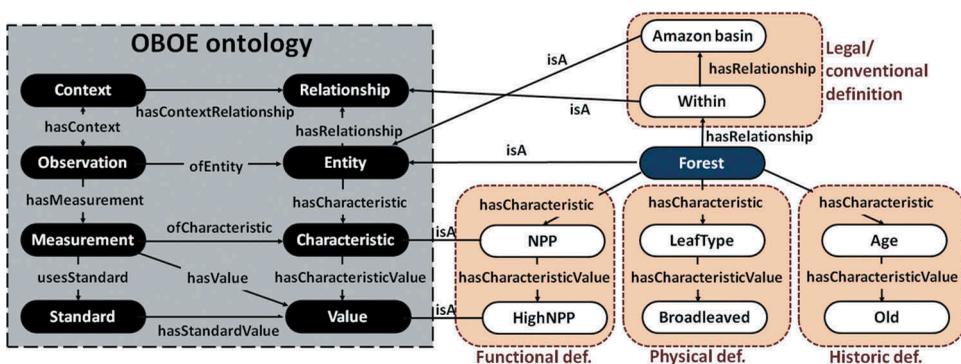


Figure 4. An example of extending the OBOE ontology to describe the concept of “forest” according to different modes of definitions. In that example, “forest” is an “Entity” (according to OBOE) that is described based on some “Characteristic” (“NPP,” “LeafType” or “Age”) and associated values (“HighNPP,” “Broadleaved” or “Old,” respectively). Finally, the “forest” can also be defined according to its spatial relation (e.g. “within”) with another “Entity” (e.g. “Amazon basin”). The colour version of this figure is available on the on-line journal paper.

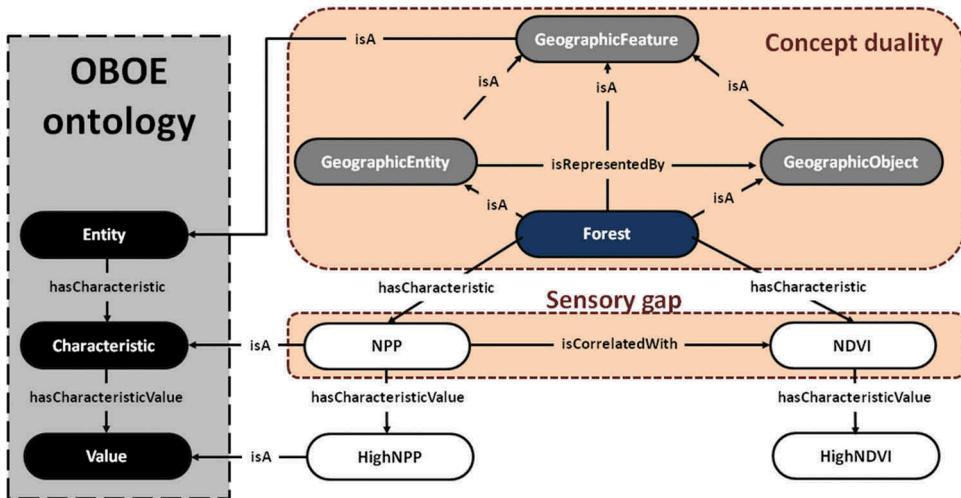


Figure 5. An example of extending the OBOE ontology to describe definitions of a single geographic concept as observed from a real-world vs. an image perspective. Here the ontology enables to explicit the difference between geographic features, geographic entities and geographic objects, thus clarifying the concept duality issue. It also allows to describe the relationships between characteristics (e.g. NDVI is correlated to NPP) thus reducing the sensory gap. The colour version of this figure is available on the on-line journal paper.

data mining principles. These are particularly useful if the data are poor, irregular or incomplete.

On the other hand, formal ontologies are based on the open world assumption (OWA), which makes it easier to handle partial definitions of vague concepts. The OWA works under the assumption that knowledge of the world is incomplete so that anything is true or false unless the contrary can be proved (Falomir et al. 2011). For example, two concepts overlap unless they are declared as disjoint, or a fact that does not belong to the knowledge base cannot be considered to be false. OWA is quite new to remote sensing experts whose methods are usually based on the closed world assumption (CWA). Indeed, a set of classes of interest is usually defined a priori (in case of supervised classification) and all pixels or image objects are assigned to one (and only one) of these classes. While this approach may be appropriate for broad land cover classes (e.g. vegetation, water, bare soil, etc.), it may be conceptually limited to map finer classes. For instance, Arvor et al. (2011) mapped five classes of cropping practices (two single-cropping classes based on soybean or cotton and three double-cropping classes based on soybean and maize or millet or cotton) in Mato Grosso based on MODIS time series of vegetation indices. While these five classes do account for a large proportion of the total cropland area, the fact is that other cropping practices do exist in the study area (e.g. triple-cropping practices, crop-livestock integration). Although monitoring these classes with low representation was not required to analyze the agricultural dynamics at the regional scale, classifying all the pixels of cultivated areas in one of the five classes of cropping practices is, as a matter of fact, false. An ontology-based approach using knowledge-based descriptions of these five classes would not have taken any decision on the pixels in the classes with low representation, which may seem problematic from an

operational point of view (e.g. it is difficult to analyze the spatial dynamics if all the pixels are not classified) but, from a conceptual point-of-view, is actually more correct.

Nonetheless, it is worth noting that closed world semantics may be required in some cases when the set of relevant facts is known. For example, if a user needs to recognize a plane in a remote sensing image, the following rule “a plane has a head, a tail and two wings” cannot be used in OWA. Since the world is not closed, counting one head or two wings is not allowed. If counting is important for the domain application, then a solution explored in the literature has been to extend the semantics of OWL with non-monotonic features such as integrity constraints (Tao et al. 2010a, 2010b). Thus, standard OWL axioms are used to obtain new inferred knowledge with open world semantics whereas integrity constraints validate instances using closed world semantics. Nevertheless, the use of these rules may lead to undecidability, so their expressiveness has to be restricted (Motik, Sattler, and Studer 2005; Krötzsch, Rudolph, and Hitzler 2008). Another solution consists in restricting/closing the world for each particular image by adding extra axioms (Falomir et al. 2011), that is, to make it explicit that one wing/head/tail belongs to a particular plane and that it does not belong to any other plane in the image. Note that OWL individuals must be explicitly defined as being different from the corresponding axioms, otherwise they may be considered as the same fact since OWL does not follow the Unique Name Assumption (UNA) (see Falomir et al. (2011) for more details).

3.3. *Ontologies to manage and share knowledge about the interpretation of remote sensing images*

Although both symbolic and numeric knowledge can be represented in formal ontologies, the focus is clearly on the symbolic knowledge (e.g. “Forest” has “HighNPP” or «“HighNDVI” values) rather than numeric knowledge (e.g. Forest = NDVI > 0.6). It thus differs markedly from traditional approaches in remote sensing where the knowledge is implicitly contained in image processing tasks, as in an image analysis processing chain where a rule like NDVI > 0.7 refers to the computation of a vegetation index associated with a comparison operator (greater than). In this case, the knowledge turns out to be a new datum, separated from the image and the associated processing tasks, that can be handled and shared easily.

Working with symbolic knowledge independently from numeric knowledge enhances knowledge management. It is possible to formalize a few pieces of knowledge (e.g. concepts and relations) without affecting the entire conceptualization (whereas changing a rule in an image analysis and processing chain may require adapting all its child processes). It also facilitates collaborative and interdisciplinary research by connecting concepts from different scientific domains (in ecology, agriculture, geo-health etc.). Further, the users can evaluate the fitness for use of the resulting remote sensing products.

Improved knowledge management also enhances knowledge sharing. For example, to share classification rules implemented in an image processing chain means sharing a set of processing tasks that have proven to be efficient for a defined remote sensing dataset. Colleagues who wish to reuse the processing chain then will need to adapt it to their own dataset. To do so, they will need to “capture” the symbolic knowledge triggered by the person who initially implemented the processing chain (but did not make his/her symbolic knowledge explicit) in order to build new numeric knowledge (e.g. to set down new rules with thresholds) better suited for their case studies. In this regard, different users may have different interpretations of the implicit symbolic knowledge contained in the same processing chain. With formal ontologies, it is possible to limit the subjectivity of

the remote sensing analysis by directly sharing the symbolic knowledge through OWL repositories handled by semantic data stores (e.g. Jena TDB or Sesame). Jena TDB allows for example users to store domain knowledge using OWL formalism. Stored domain knowledge can be queried using the CRUD operations (Create, Retrieve, Update, Delete). These OWL repositories represent a new modular interdisciplinary contextual knowledge base about ever more diverse remote sensing applications and may turn out to be a new object of research per se.

Finally, the explicit specification of the knowledge used to extract information from remotely sensed data allows the integration of remote sensing classification products from other information sources. Interoperability is a major advantage of Ontology-RSA, especially in a context in which the technical focus has moved from the accuracy of the remote sensing information extraction and inventory to fitness for the purpose of integration of various spatial sources of information in support of specific policy goals (GEO's goal 2016–2025).

4. Designing ontologies for remote sensing applications

Designing Ontology-RSA is a complex task. this section discusses two research directions to be considered by ontology designers interested in remote sensing applications.

4.1. *Ontologies, spatial reasoning, and cognitive semantics*

Knowledge representation in formal ontologies must approach experts' cognitive semantics to capture how humans conceptualize geographic features. However, not all the formal ontologies used in the geographic domain include spatio-temporal information (Kuhn, Raubal, and Gardenfors 2007). In this paper, let us recommend considering the principles of naive geography (Egenhofer and Mark 1995) and cognitive geography (Couclelis 1992) when defining ontologies. Naive Geography refers to a set of theories on how people intuitively or spontaneously conceptualize geographic space and time (Egenhofer and Mark 1995; Freundschuh and Egenhofer 1997). Cognitive geography refers to the way humans understand, categorize and act in the geographic world (Couclelis 1992). Some principles of cognitive geography are proposed in Couclelis (1992) as a conceptual framework to explain the logical reasoning triggered by humans to recognize geographic features. Ontologies align numerical data with expert knowledge and allow common sense categorizations by running algorithms based on expert conceptualizations. Thus, so that formal ontologies can be widely used by remote sensing experts, they must be well designed by engineers and they must approach the experts' semantics – approaching their way of thinking – in order to facilitate their work. This is the reason why formal ontologies must take cognitive issues into account in their engineering design.

As mentioned by Kuhn, Raubal, and Gardenfors (2007), applying cognitive semantics in the design of spatio-temporal ontologies remains a challenge. The conceptual spaces defined by Gärdenfors (2000, 2014) have been widely adopted. Prototype theory was introduced more recently (Fiorini, Gärdenfors, and Abel 2014; Lieto et al. 2015). However, to our knowledge, other cognitive concepts such as image schemas and concept blending have not been yet applied to ontology engineering.

Kuhn, Raubal, and Gardenfors (2007) underlined that, in order to be more cognitive, geospatial ontologies should:

- (1) be grounded by establishing meaningful and suitable primitives;
- (2) consider space and time not only as application domains but foundational aspects of ontology due to their correlation with human conceptualizations;
- (3) be process-oriented, not static structures;
- (4) integrate realistic semantics (formal models of truth) and cognitive semantics (meaning for individuals);
- (5) allow perspectivalism and relativism, as multiple granularities are allowed in spatial domains;
- (6) consider conceptual mappings (i.e. including conceptual blending) so that the system can adapt the semantics of its concepts to the user's semantics, which will enhance human-computer interaction,
- (7) allow personalization, since users' information needs to relate to the situational and personal context.

Qualitative Spatial and Temporal Representations and Reasoning (QSTR) (Cohn and Renz 2007; Ligozat 2011) models and reasons about time (i.e. coincidence, order, concurrency, overlap, granularity) and also about properties of space (i.e. topology, location, direction, proximity, geometry, intersection) and their evolution over time between continuous neighboring situations. Maintaining the consistency and constraints in space and time are the basics in qualitative reasoning when solving spatial problems (i.e. path finding, orientation, relative position, etc.) and temporal problems (i.e. constraint satisfaction, schedule optimization, precedence). As a result, well-defined qualitative models and reasoning techniques have appeared in the literature that can deal with imprecise and incomplete knowledge on a symbolic level. Geographic Information Science, in particular, has been the field in which most QSTR models have been applied, for example, Allen's Temporal Interval Relations calculus (Allen 1983), Region Connection Calculus (RCC) (Randell, Cui, and Cohn 1992), 9-Intersection model (Egenhofer 1995), etc. In the literature, examples of research works in GIS can be found in which formal ontologies are defined taking qualitative spatial reasoning models into account: the spatio-temporal ontology for representing the changing of historical places developed by Hyvönen et al. (2011); a high-level conceptual metamodel, based on QSR approaches that can be used in the remote sensing domain as a framework to formalize spatio-temporal knowledge (Pierkot et al. 2013); a method to perform qualitative spatial reasoning in geospatial representations explicitly formalized by means of an application ontology proposed by Torres et al. (2016). In other fields, such as robotics and computer vision, other approaches have also dealt with the challenge of building a description-logics ontology using qualitative spatial concepts for digital image categorization (see QImageOntology by Falomir et al. 2011).

QSTR models facilitate human-machine interaction because they align human cognitive concepts with numerical perceptions of computational systems. Another advantage of a description based on qualitative spatial relations is that a semantic meaning can be assigned to them by means of logics and formal ontologies. In sum, formal models of semantics (e.g., ontologies) can become meaningful for human experts/engineers if they become more cognitive. Space and time do play a foundational role in explaining and representing meaning. QSTR models can provide a solid grounding for designing formal ontologies about space and time, allowing standardization and formalization of application ontologies. Formalisms as conceptual spaces and prototypes have to be taken into account to approach the experts' way of thinking since they best capture cognitive

semantics. More research is needed to integrate other cognitive theories such as concept blendings and image schemas in ontology modelling.

4.2. *Top-down vs bottom-up approaches*

According to the definition introduced in [section 3](#), formal ontologies are intended to represent consensual knowledge in order to facilitate knowledge sharing. It is consequently usually advised to implement collaborative domain ontologies using a top-down approach. Experts from a scientific domain such as remote sensing would then be expected to get together and define how they interpret satellite images. But reaching a consensus about classification rules to map vague geographic features seems illusory. This is why Janowicz (2012) proposed “a radical paradigm shift in ontology engineering away from a small number of authoritative, global ontologies developed top-down, to a large number of local ontologies that are driven by application needs and developed bottom-up based on observation data.” In fact, both approaches should be considered as complementary and necessary, giving ontologies an essential role in the articulation of knowledge- and data-driven approaches in remote sensing.

Top-down approaches are needed to design a collaborative framework ontologies that provide definitions for general purpose terms and act as a foundation for interconnecting more specific domain ontologies (Madin et al. 2008). In the context of Earth Observation, relevant framework ontologies should include general concepts concerning observations for describing the earth’s environment ([Figure 5](#)). For example, and as mentioned earlier, an ontology such as OBOE is designed to capture the semantics of scientific observations and can thus be used to describe both real-world geographic entities and their corresponding geographic objects ([Figure 6](#), top left). OBOE was first designed for ecological applications (Madin et al. 2008) but can be adapted for other applications including remote sensing (Andrés et al. 2014). The O&M ontology, known as “omlite,” is another ontology dedicated to the description of observations and measurements based on ISO/OGC standards (Cox 2013). OBOE and O&M ontologies can be aligned together, considering a Measurement in OBOE as the equivalent class of Observation in O&M (Cox 2013). Both ontologies can also be connected to the Semantic Sensor Network (SSN) ontology that provides a framework to describe sensors and their observations (Compton et al. 2012; OGC 2017a) ([Figure 6](#), bottom left). The SSN ontology can support a wide range of applications including satellite imagery. Ontologies dedicated to the representation of spatial relations also exist (Kong et al. 2003; OGC) ([Figure 6](#), top center). Regarding the Earth Environment domain, the Semantic Web for Earth and Environmental Terminology (SWEET) proposed by NASA may be an appropriate framework ontology (Raskin and Pan 2005; SWEET 2017) ([Figure 6](#), top right). This ontology is composed of nine modular ontologies that make it possible to describe any compound concept related to the environment (Tripathi and Babaie 2008). For example, the concepts of “Forest” and “Net Primary Productivity” are defined and could be interconnected to provide the description of a forest as described in our example. Ontologies such as OBOE, O&M, SSN, SWEET can be interconnected and extended to include additional concepts more specific to the remote sensing domain, including the elementary concepts remote sensing experts rely on to interpret remote sensing images (e.g. concepts related to spectral bands, spectral or textural indices) Examples of such remote sensing ontologies have already been implemented (Gu et al. 2017; Andrés et al. 2017) but have not been related to any upper ontology to date ([Figure 6](#), bottom right).

While a top-down approach is suitable to design framework ontologies in order to set down a reference conceptualization for the description of geographic features, bottom-up

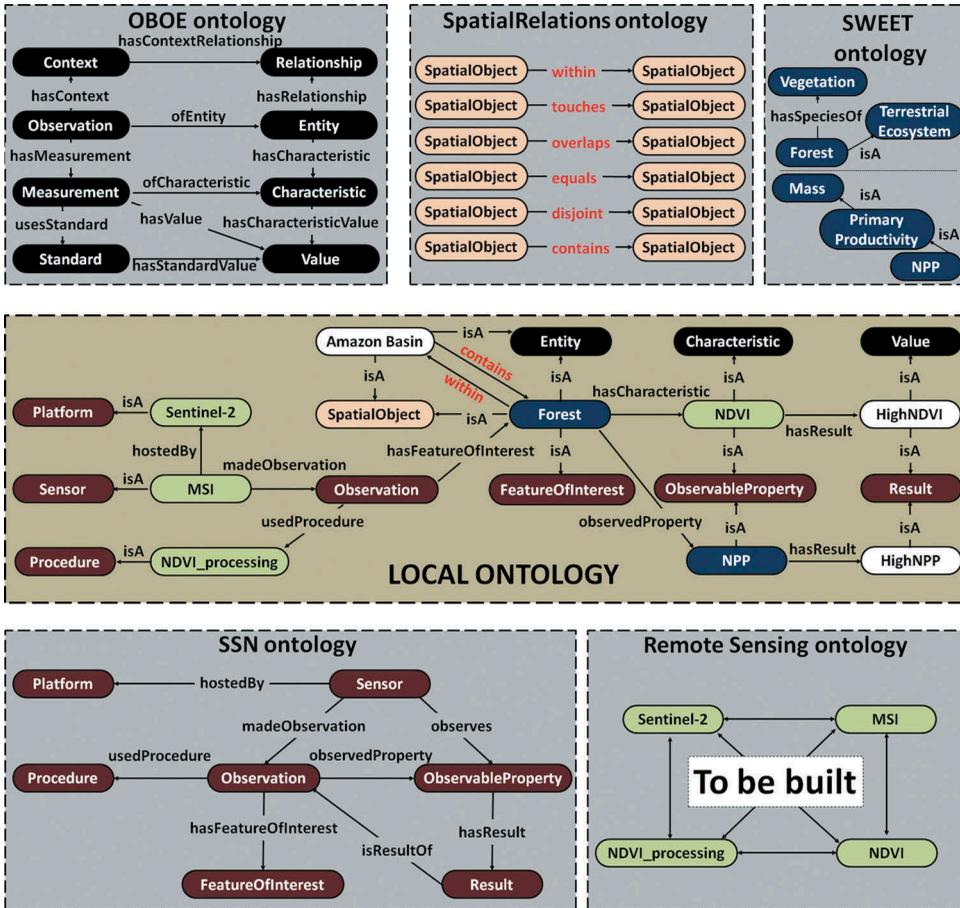


Figure 6. Illustration of a local ontology created to describe the concept of “Forest.” The description is done by extending upper level ontologies. Concepts of already existing ontologies (e.g. OBOE, Spatial Relations, SWEET, SSN ontologies) are reused for this specific application while concepts from the remote sensing domain (e.g. NDVI, Sentinel-2), etc) need to be described in a Remote Sensing ontology (to be built). The colour version of this figure is available on the on-line journal paper.

approaches are necessary to allow remote sensing scientists to formalize their expert contextual knowledge in a local ontology (Andrés et al. 2017; Falomir et al. 2011). In our example, experts may rely on framework formal ontologies to make their knowledge explicit about (1) the relation between NDVI and NPP and (2) the classification rule implemented to detect forest objects (e.g. Forest = NDVI > 0.7) (Figure 6, central part). At a time when data-driven approaches are gaining ground due to the increasing availability of remote sensing data, exporting models of statistical approaches (e.g. decision trees) into numerous local ontologies would facilitate the sharing of such contextual knowledge with colleagues from remote sensing and other scientific domains. Such local ontologies correspond to studies by Belgiu et al. (2014) or Rajbhandari et al. (2017) for example.

5. How to comprehend the advantages of ontologies for the remote sensing community?

Implementing Ontology-RSA implies addressing many technical and conceptual issues such as the issues of scale, the vagueness of geographic terms that are specific not only to remote sensing domain, but also to other domains such as GIS or ecology. Therefore, a formal ontology addressing these issues can benefit different domains where the big data era challenges the transformation of the existing data into knowledge (Arvor et al. 2013). But, to date, the main difficulty facing ontology experts is convincing the remote sensing community that formal ontologies can enhance their scientific domain. Like in the early days of ontology-based applications in ecology, when ontologies appeared to be an esoteric topic for ecologists (Madin et al. 2008), the points discussed in the previous section may appear to be somewhat abstruse and philosophical, from a remote sensing perspective. A pragmatic way to guide remote sensing experts could be to answer a few questions they often raise when trying to comprehend the advantages of using ontologies to interpret satellite images.

5.1. Can ontologies be compared with other traditional classification methods?

Since image classification is a major application for ontologies in remote sensing, the advantage of ontologies when compared with existing classification methods (e.g. Support Vector Machine (Mountrakis, Im, and Ogole 2011), Random Forest (Belgiu and Dragut 2016) or deep learning (Zhu et al. 2017) is often questioned. In fact, ontologies are used together with semantic classifiers (called reasoners) that should not be compared with other traditional classifiers based on statistical approaches (although reasoners could be used to classify images containing numeric data). Ontologies are implemented to deal with symbolic knowledge, while statistical classifiers process the numeric data to produce numeric knowledge (e.g. to define a set of classification rules from a decision tree approach). Despite the fact that the statistical classifiers are merely data-driven approaches, remote sensing experts have to make use of a priori symbolic knowledge when collecting training samples that are representative for the classes of interest. As this paper shows, an Ontology-RSA dealing with image classification approximates a rule-based classifier in which rules are defined by experts. Consequently, to compare a classification produced using an ontology-based approach with another one produced by a supervised classification (SVM or deep learning for example) is like assessing the interest of a knowledge-driven approach (as in a rule-based classification) as opposed to a data-driven approach (as in a supervised classification). Although of interest, this issue does not involve a discussion of ontologies.

5.2. Why use ontologies rather than a rule-based classification approach?

Since an Ontology-RSA dealing with image classification is an approximation of a rule-based classifier, one may question the advantage of using ontologies over a rule-based classifier using the same knowledge. As already demonstrated by Rajbhandari et al. (2017) in a study dedicated to landslide mapping based on remote sensing images, ontology-based classification and rule-based classification approaches perform similarly. The difference is that the ontology stores both the symbolic and numeric knowledge in a way that allows the domain expert knowledge (i.e. the symbolic knowledge) to be formalized separately from the image processing tasks (i.e. the numeric knowledge that is

only valid in a specific context). This is quite different from traditional rule-based approaches in which the image analysis and processing chain only contain numeric knowledge, i.e. an implicit representation of symbolic knowledge. Overall, it means that, in an ontology-based approach, the innovation is not rooted only in the knowledge content per se (i.e. the classification rules), but in the way, the knowledge is represented and formalized, i.e. the way the ontology has been designed to appropriately represent expert knowledge. Although ontologies theoretically represent consensual knowledge, various ontologies may coexist for similar domains. This means that there may be as many ontologies as remote sensing experts, with similar knowledge (e.g. the same classification rules), but different approaches to modelling it. For instance, OBOE and O&M are two framework ontologies to describe scientific observations that are modeled differently even though they involve certain (but not all) equivalent concepts.

Additionally, expressing symbolic and numeric knowledge in formal ontologies has many advantages: (1) users can get insights into data provenance (data lineage) and can evaluate the fitness of the resulting classification for their own purpose; (2) the semantics of the target classes such as land cover classes are explicitly specified and therefore, heterogeneous classification products can be easily integrated and harmonized across distributed networks and communities (Espinoza-Molina et al. 2015). The semantic heterogeneity of land cover classifications has been intensively discussed in the last years (Herold et al. 2006; Jansen, Groom, and Carrai 2008), mainly because land cover products are used to derive additional information on various environmental conditions: e.g. greenness index evaluation. Therefore, the semantics of land cover classes and the protocol that turns data into information needs to be transparent to the users (Comber, Fisher, and Wadsworth 2005); (3) the consistency of the formal ontologies can be automatically verified by the reasoner mechanisms; (4) similarities between different ontologies can be easily measured.

As defined by Phinn (1998), the information types to be extracted from remote sensing data are: landscape structure, landscape composition and biophysical properties. In our paper, we focused extensively on land use/land cover classification. However, landscape structure and biophysical properties can also be included in an Ontology-RSA. For example, the definitions of the biophysical variables can be explicitly specified by e.g. specifying a biomass formula defined as a function of remote measurements. The definition of the biophysical properties will further influence the selection of the proper measurement techniques, i.e. sensors and their characteristics in terms of the spatial, spectral, radiometric or temporal resolutions capabilities. These characteristics can also be explicitly specified in the Ontology-RSA.

5.3. How do the ontologies improve the classification results?

The overall contribution of ontologies should not be measured only with the traditional techniques used in remote sensing such as overall accuracy or the Kappa index (Congalton 1991). From an image processing perspective, all the results produced by an ontology-based approach could perhaps have been achieved with any traditional image processing software (e.g. setting classification rules in any GEOBIA software), as long as the knowledge triggered to process the images is similar to the knowledge represented in the ontology. In this regard, one could consider that ontologies are mere duplications of the state-of-the art knowledge-based image classification, except in that they use another way of representing image interpretation knowledge but without improving the results. However, although the accuracy of classification is not improved,

this does not preclude the improvement of the entire remote sensing approach. The first objective of an ontology-based approach is not necessarily to produce better remote sensing-based classifications with better overall accuracy or Kappa index. Such measures of accuracy show how relevant remote sensing expert knowledge (expressed as numeric knowledge) is to classify an image, i.e. to produce the best possible approximation of reality. However, as emphasized previously, the innovation in an ontology-based approach does not lie only in the knowledge content, but in the way the knowledge is represented and deployed in the ontology. This involves that the ontology-based approach should not be assessed only by analyzing the quality of the final classification. In fact, checking whether a map produced using an ontology-based approach is similar to a classification produced by another more traditional image analysis approach is a good way to check that the ontology is a reliable representation of the expert knowledge, which is a positive result from an ontological perspective. It is also worth mentioning that even when comparing two ontology-based approaches based on the same knowledge, attention should not be focused on the result of the classification, but on other characteristics of the ontology. Different metrics can be used to assess the quality of the developed ontology (Ma et al. 2018) including structural metrics (formalization, structural accuracy, consistency, cohesion, domain coverage), functional adequacy (controlled vocabulary, inference, precision etc.), compatibility (portability and adaptability), operability (appropriateness, or ease of use), maintainability (modularity, reusability etc.) or quality in use (efficiency, effectiveness, flexibility etc.) (Duque-Ramos et al. 2014).

6. Conclusion

Whereas remote sensing science is evolving rapidly with the advent of artificial intelligence mainly based on deep learning for data-driven applications, let us recommend that the community should pay more attention to Good Old-Fashioned Artificial Intelligence (GOFAI), e.g. artificial intelligence based on mathematics and logic to produce symbolic representations of abstract concepts (Marcus 2018), to accompany the development of knowledge-driven approaches and facilitate the emergence of hybrid approaches. In this regard, formal ontologies have a great potential to advance remote sensing in the long term by addressing the important conceptual limitations of the traditional approaches used in remote sensing science. More specifically, formal ontologies allow making explicit the expert knowledge used to interpret remote sensing images, splitting it into symbolic and numeric knowledge. Therefore, formal ontologies address the complexities of image interpretation tasks separately from the thematic knowledge about geographic concepts. In so doing, formal ontologies improve the sharing and re-use of formalized remote sensing expert knowledge with the scientific community at large, including scientists from other fields of application. Although formal ontologies do not necessarily improve the image analysis process in terms of classification accuracy (which the remote sensing community might consider a priority), their main asset is intra-domain and inter-domain knowledge sharing and re-use. Formal ontologies can be easily integrated into other knowledge infrastructure dedicated to information sharing and integration and help to reduce the gap between remote sensing science and the fields of application, e.g. ecology, urbanism, agriculture or geo-health, among others. Ontologies thus represent a great opportunity to support interdisciplinary science through better representation and management of scientific knowledge. As remote sensing science is fundamentally interdisciplinary, it should benefit from such innovative technologies. However, formal

ontologies are still often looked on as a buzzword by the remote sensing community and further advances are needed to enable a real paradigm shift.

Firstly, better practices need to be supported. For example, qualitative spatial models are mathematically well-formalized and they have been already tested in GIS. So let us recommend to use these models when modelling knowledge about time (i.e. coincidence, order, concurrency, overlap, granularity) and also about space (i.e. topology, location, direction, proximity, geometry, intersection) because their corresponding reasoning calculus has been already developed and can be used by ontology reasoners.

Secondly, although numerous ontologies have been implemented in different scientific domains (some with particular emphasis on the description of spatio-temporal features), remote sensing ontologies are still lacking. Of course, there are a few examples of ontology-based remote sensing applications but they remain poorly connected to upper level ontologies. In a certain way, they are nothing more than local prototypes illustrating the potential ability of ontologies to advance remote sensing. It is thus urgent to produce collaborative domain ontologies especially dedicated to remote sensing science, including concepts about sensors, image features (e.g. spectral indices, textural indices, etc.) and image processing tasks. This is a necessary step to generalize the development of numerous local but integrated (i.e. connected to upper level ontologies) ontology-based applications.

Thirdly, once remote sensing domain ontologies are built, the next challenge consists in “producing” the knowledge to be represented in these connected local ontologies. To this end, it is necessary to facilitate access to ontologies by remote sensing experts. Promoting ontology engineering courses in remote sensing education programs and developing ontological extensions in image processing software (especially in GEOBIA software) is essential to ensure the adoption of Ontology-RSA by remote sensing experts. In addition, implementing procedures to capture the knowledge derived from machine learning applications and automatically populate local ontologies is a promising way forward to accumulate knowledge. In so doing, “big data” in remote sensing will not only become an issue of “big EO data” processing but also of “big knowledge data” management. In this regard, ontologies should definitely play a pivotal role at the articulation between knowledge- and data-driven approaches, thus contributing to the unification of remote sensing science considering both data- and knowledge-driven approaches.

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