TeMA

Journal of
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This special issue collects a selection of peer-review papers presented at the 8th International Conference INPUT 2014 titled “Smart City: planning for energy, transportation and sustainability of urban systems”, held on 4-6 June in Naples, Italy. The issue includes recent developments on the theme of relationship between innovation and city management and planning.

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PLANNING FOR ENERGY, TRANSPORTATION AND SUSTAINABILITY OF THE URBAN SYSTEM

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TeMA

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Journal of
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This special issue of TeMA collects the papers presented at the 8th International Conference INPUT 2014 which will take place in Naples from 4th to 6th June. The Conference focuses on one of the central topics within the urban studies debate and combines, in a new perspective, researches concerning the relationship between innovation and management of city changing.

TeMA Journal of Land Use, Mobility and Environment

EIGHTH INTERNATIONAL CONFERENCE INPUT 2014

SMART CITY. PLANNING FOR ENERGY, TRANSPORTATION AND SUSTAINABILITY OF THE URBAN SYSTEM

This special issue of TeMA collects the papers presented at the Eighth International Conference INPUT, 2014, titled "Smart City. Planning for energy, transportation and sustainability of the urban system" that takes place in Naples from 4 to 6 of June 2014.

INPUT (Innovation in Urban Planning and Territorial) consists of an informal group/network of academic researchers Italians and foreigners working in several areas related to urban and territorial planning. Starting from the first conference, held in Venice in 1999, INPUT has represented an opportunity to reflect on the use of Information and Communication Technologies (ICTs) as key planning support tools. The theme of the eighth conference focuses on one of the most topical debate of urban studies that combines , in a new perspective, researches concerning the relationship between innovation (technological, methodological, of process etc..) and the management of the changes of the city. The Smart City is also currently the most investigated subject by TeMA that with this number is intended to provide a broad overview of the research activities currently in place in Italy and a number of European countries. Naples, with its tradition of studies in this particular research field, represents the best place to review progress on what is being done and try to identify some structural elements of a planning approach.

Furthermore the conference has represented the ideal space of mind comparison and ideas exchanging about a number of topics like: planning support systems, models to geo-design, qualitative cognitive models and formal ontologies, smart mobility and urban transport, Visualization and spatial perception in urban planning innovative processes for urban regeneration, smart city and smart citizen, the Smart Energy Master project, urban entropy and evaluation in urban planning, etc..

The conference INPUT Naples 2014 were sent 84 papers, through a computerized procedure using the website www.input2014.it . The papers were subjected to a series of monitoring and control operations. The first fundamental phase saw the submission of the papers to reviewers. To enable a blind procedure the papers have been checked in advance, in order to eliminate any reference to the authors. The review was carried out on a form set up by the local scientific committee. The review forms received were sent to the authors who have adapted the papers, in a more or less extensive way, on the base of the received comments. At this point (third stage), the new version of the paper was subjected to control for to standardize the content to the layout required for the publication within TeMA. In parallel, the Local Scientific Committee, along with the Editorial Board of the magazine, has provided to the technical operation on the site TeMA (insertion of data for the indexing and insertion of pdf version of the papers). In the light of the time's shortness and of the high number of contributions the Local Scientific Committee decided to publish the papers by applying some simplifies compared with the normal procedures used by TeMA. Specifically:

- Each paper was equipped with cover, TeMA Editorial Advisory Board, INPUT Scientific Committee, introductory page of INPUT 2014 and summary;
- Summary and sorting of the papers are in alphabetical order, based on the surname of the first author;
- Each paper is indexed with own DOI codex which can be found in the electronic version on TeMA website (www.tema.unina.it). The codex is not present on the pdf version of the papers.

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FORMAL ONTOLOGIES AND UNCERTAINTY

IN GEOGRAPHICAL KNOWLEDGE

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ABSTRACT

Formal ontologies have proved to be a very useful tool to manage interoperability among data, systems and knowledge. In this paper we will show how formal ontologies can evolve from a crisp, deterministic framework (ontologies of hard knowledge) to new probabilistic, fuzzy or possibilistic frameworks (ontologies of soft knowledge). This can considerably enlarge the application potential of formal ontologies in geographic analysis and planning, where soft knowledge is intrinsically linked to the complexity of the phenomena under study.

The paper briefly presents these new uncertainty-based formal ontologies. It then highlights how ontologies are formal tools to define both concepts and relations among concepts. An example from the domain of urban geography finally shows how the cause-to-effect relation between household preferences and urban sprawl can be encoded within a crisp, a probabilistic and a possibilistic ontology, respectively. The ontology formalism will also determine the kind of reasoning that can be developed from available knowledge.

Uncertain ontologies can be seen as the preliminary phase of more complex uncertainty-based models. The advantages of moving to uncertainty-based models is evident: whether it is in the analysis of geographic space or in decision support for planning, reasoning on geographic space is almost always reasoning with uncertain knowledge of geographic phenomena.

KEYWORDS

Formal Ontologies, Uncertainty, Geographic Knowledge, Probabilistic Ontologies, Possibilistic Ontologies, Fuzzy Ontologies

1 INTRODUCTION

Formal Ontologies have proved to be a very useful tool to manage interoperability among data, systems and knowledge. In the era of Big Data and Volunteer Geography Information (Goodchild, 2007), the issue of interoperability is definitely present and we need to face with several semantic problems. Ontologies can be used to solve these problems and help us to formalize knowledge in a more precise and explicit way. Many authors already applied ontologies to planning and geography domain (Fonseca et al. 2005; Caglioni et al., 2007, 2012; Ban et al., 2009; Murgante et al., 2011). It is part of human nature the desire to classify all the elements of nature, so that the elements of a same class correspond to similar properties. Unfortunately, in this wide and complex domain, we cannot strictly define a concept without considering uncertainty, vagueness, incompleteness, imprecision of the data and, more in general, subjective expert knowledge.

Our ability to precisely describe a system is an inverse function of its complexity (Bouchon-Meunier, 1994). Nowadays we are aware of the fact that the majority of geographic systems are complex by nature. Studying complex systems means to deal with data which can be vague (high cost), imprecise (measuring approximately 3 to 5 feet), affected by errors of various kinds (instrumental, methodological, statistical, human), ill-defined (strong pain), whose validity is not absolute (in 90% of cases) or with elements of knowledge which are intrinsically uncertain (experts think that, probably, tomorrow it will be rainy).

In the classical theory of measure we are conscious of the fact that the measure cannot provide valuable information on the judgment of the person who measures, but the latter is not sought after as it is considered spurious knowledge in regard to the phenomenon under observation. The main goal of the theory of measure is to assess the degree of imperfection of information provided within an objective measurement process. In the past, reference was made to the error theory, but this approach, based on the assumption of knowability of the "real value", given a long series of measurements (where frequencies approximate probabilities) and an underlying theoretical probability distribution, has its own flaws and cannot always been applied to many real world situations (especially when studying social systems). Today we refer to uncertainty approaches, based on subjective judgments by experts and sound mathematical theories, capable of dealing with such judgments. Subjective Bayesian probability theory has traditionally been the first attempt to overcome the assumptions of frequentist probabilities. However, even the methods based on Bayesian probability theory have their own limits in this regard, as expert knowledge does not always respect the stringent requirements of probability axioms. Newer theories have thus emerged in the course of decades.

Possibility theory, introduced in 1978 by L.A. Zadeh and subsequently developed by H. Prade and D. Dubois (1985), provides a framework that allows treating the concepts of non-probabilistic uncertainty, and gives the opportunity, within the same formalism, to deal with imprecision-related uncertainty. Zadeh is also the founder of fuzzy logic (1965), capable of representing gradual belonging of elements to a given set and of reasoning about gradual belongings.

Both possibility theory and probability theory can be seen as particular restrictions of a common and more general theory: the *evidence theory* of Dempster and Shafer (1968, 1976). According to this theory, an individual can make a judgment, assign a degree, with which he quantifies the evidence of a given atomic statement: this is the mass of belief that he would assign to that statement. More complicated statements are evaluated in two different ways. The degree of plausibility of the statement is the sum of the belief masses of all the atomic statements which are not in contradiction with it. Its degree of belief is the sum of the belief masses of all the atomic statements which are strictly included in the more general statement. The probability of the statement lies between its belief ant plausibility degrees. Whenever additive belief masses (which sum to one) cannot be determined, plausibility and belief degrees correspond to the possibility and necessity measures of possibility theory, and probabilistic triangular norm (product) and co-norm (sum) are replaced by possibilistic equivalents (min and max, respectively).

The use of imprecise, vague or uncertain knowledge leads to think in a more flexible way than what we could do with classical logic. In particular, probabilistic, fuzzy, possibilistic or evidential frameworks can respond to certain needs in geographic knowledge:

- treating intermediate values of truth between true and false absolutes;
- modifying the concept of quantifiers like universals and existentials;
- introducing into propositional logic probability, possibility, belief or truth of a statement;
- using new rules of inference, of reasoning, different from the *modus ponens* and *modus tollens* of classical logic.

In this paper we will show how formal ontologies, as well, can evolve from a crisp, deterministic framework (ontologies of hard knowledge) to new probabilistic, fuzzy, possibilistic or evidential frameworks (ontologies of soft knowledge). This can considerably enlarge the application potential of formal ontologies in geographic analysis and planning, where soft knowledge is intrinsically linked to the complexity of the phenomena under study.

1.1 UNCERTAINTY

Geographic Information Systems allow management of large information volumes about geographic objects, as administrative units, buildings, networks and natural environments, past and present. This knowledge is subjected to various forms of uncertainty, or imperfection if we talk about data (de Runz, 2008). If this uncertainty is dismissed in the representation of data, the validity of results, of the generalization process, and of relationships linking geographic objects can be questioned. Thus, uncertain information impacts the quality of analysis and decisions.

Referring to Fisher et al. (2005) and de Runz (2008), we can distinguish whether the classes of concepts are well or ill defined (Fig. 1). Cases where concepts and classes are well defined are more easily dealt with probabilistic approaches. We are often here in cases of shallow uncertainty (Walker et al. 2003), where a consensus exists on the probabilistic model to be used. In the other cases, concepts or classes are ill defined and data uncertainty is due to problems of inaccuracy or ambiguity. Typical modelling approaches to these medium or deep uncertainty situations (Walker et al. 2003) go beyond probability theory. Of course, the cases presented in the general scheme of Fig. 1 are pure, archetypical situations. Real case situations typically combine kinds of uncertainties, requiring hybrid and ad hoc approaches to knowledge modelling.

It should also be remarked that geographic knowledge goes well beyond geographic information. Data are only the starting point of geographic knowledge production. Much more often, geographers and planners are interested in knowing relations among phenomena. What is thus the relation among the development of a new highway network and the transformations of land-use within a given region? And what can the relationship be among the development of a new highway here and the transformation of land-use around a village 5 km away from here? These relations are often non deterministic in geographic space and eventual deterministic relationships can only be retrieved in an imperfect and messy form from the analysis of real world data. In many real case situations, even perfect data knowledge would finally result in uncertain knowledge about relations. However, this uncertain expert knowledge on relations among geographic phenomena, as well as uncertain information on empirical situations, are the bread and butter of the decision making process in urban and regional planning. Can formal ontologies provide more coherent ways of structuring this uncertain knowledge on geographic space? What kind of ontologies are better suited to facilitate knowledge interoperability (between experts and computer systems) and reasoning about this knowledge?

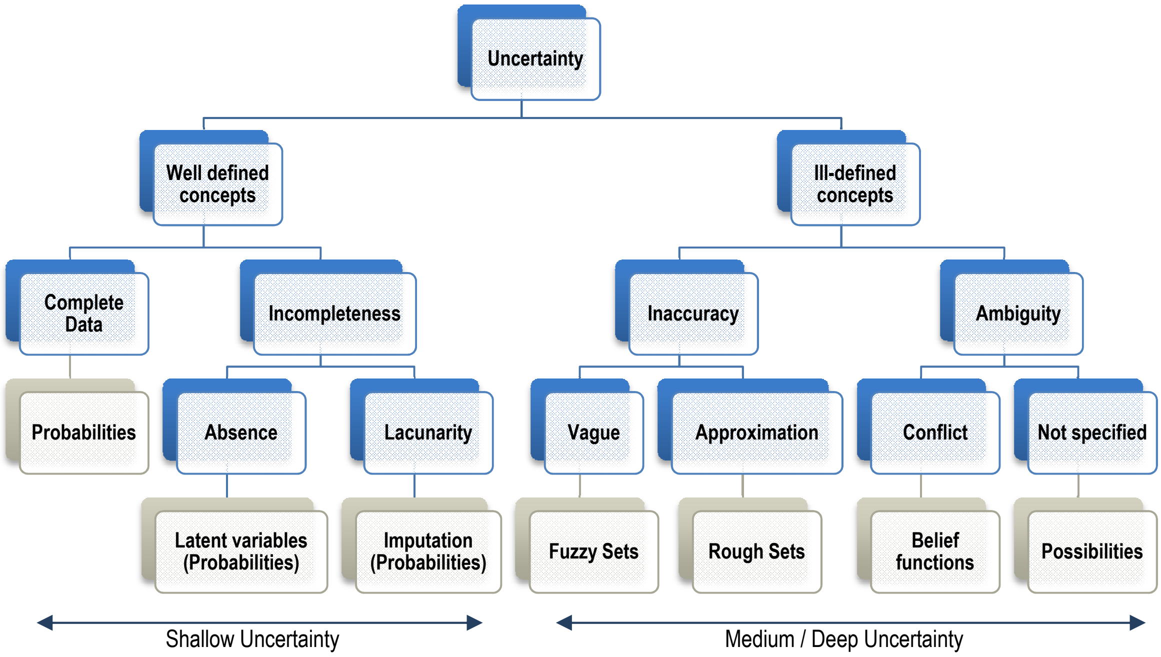

Fig. 1 Taxonomy of uncertainty in geographic information and suggestions of associated formalisms

2 UNCERTAINTY AND FORMAL ONTOLOGIES

Formal ontologies are traditionally been presented as a way to reduce uncertainty in the conceptualization phase, which is a prerequisite for geographic modelling. Through the definition of crisp concepts, medium and deep uncertainty situations can be avoided and residual uncertainty can eventually be captured through variance estimations in a given probabilistic framework. Relations among concepts are also modelled as crisp, whether dealing with taxonomies of concepts (relations like IsA, IsPartOf, etc.) or with more complex networks of relations (spatiotemporal relations, causal relations, etc.). This limits considerably the propagation of probabilistic uncertainty in modelling applications developed from such ontologies.

We don't deny the usefulness of crisp ontologies in order to eliminate unnecessary uncertainty linked to concept definitions. The problem is that geographic phenomena cannot always be conceptualised crisply and that conflicting conceptualisations could be an important component of certain domains of geographic knowledge. Moreover, relations among phenomena which are not simple taxonomies need different formal approaches (and even taxonomies could greatly benefit from non crisp ontologies). We thus need new kinds of formal ontologies capable of dealing with uncertainty, whenever uncertainty is not eliminable in the domain knowledge. Crisp ontologies should be considered as a limiting case of such soft ontologies.

Generally speaking, an ontology is an explicit formal specification of a shared conceptualization in a field of study (Studer et al. 1998). It is a conceptual model that adopts a formal protocol to enable the sharing of knowledge among experts in the field and between the latter and software. The use of formal ontologies concerns in two ways issues of uncertainty in geographical modelling.

First, ontologies define entities, properties and relations that characterize a given field of study in a formal language (including the OWL Web Ontology Language, compatible with the project of the Semantic Web). Reasoners compatibles with this language are then able to perform "automatic thoughts" with a first-order logic (more precisely descriptive logic). Imposing the use of such a formalism allows the modeller to eliminate a number of uncertainties in the conceptualization phase of his model, uncertainties associated with ambiguities, contradictions, the incompleteness in the definitions of objects, properties and relationships. Uncertainties associated with imprecise and vague definitions can be resolved in a formal ontology, but at the cost of simplifying the study domain in ternary predicates (true / false / unknown).

It is precisely to eliminate the artefact of a deterministic (or binary) logic, not really suited to model the fuzzy and uncertain relations in geographic systems, that new families of formal ontologies haves been developed: *probabilistic ontologies* (Ding and Peng, 2004), based on the language PROWL (Probabilistic Web Ontology Language, Costa et al. 2008); *fuzzy ontologies* (Abulaish et al., 2003; Straccia, 2006; Bakillah et al., 2011), based on the language Fuzzy-OWL; *possibilistic ontologies* (Loiseau, Boughanem, Prade, 2006) based on possibilistic logic (Dubois et al., 1994) and an extension of OWL language using annotation proprieties. These new ontologies are equally associated to new types of reasoners, which give us the possibility to perform automatic reasoning and classification of knowledge.

We don't want here to expose the precise formalisms of the three logics presented above, but we will present the three ontology families, which differ from the classical descriptive logic ontology, in order to better understand their main features and their advantages in formalizing geographic knowledge.

2.1 ONTOLOGY AND PROBABILISTIC LOGIC

Probabilistic logic combines the capacity of probabilistic theory to deal with uncertainty and the power of deductive logic in exploring knowledge structures. Probabilistic logic is a natural extension of traditional logic and it can be used in a wide range of application areas. Results of logical inference, or reasoning, are derived through probabilistic expressions, and above all laws of probability composition and Bayes theorem.

Bayesian Networks, also called probabilistic directed acyclic graphical models, implement Bayesian probabilistic logic and are powerful tools to represent probabilistic relationships between causes and effects. They have already been proposed as tools for modelling geographic phenomena (Fusco 2004, 2012). In their graphical representation variables corresponds to nodes of the network, and direct causal or influential relationships are represented as directed arcs between two nodes. The uncertainty of the causal relationship is locally represented by the conditional probability table, and it is described in Bayes' theorem. Under a conditional independence assumption, the graphic structure of Bayesian Network allows an unambiguous representation of interdependency between variables (Ding and Peng, 2004). Knowledge on geographic phenomena conveyed by Bayesian networks is hard to formalize with traditional crisp ontologies. This is the main reason that fostered the development of probabilistic ontologies.

Probabilistic ontologies can not only reduce the uncertainty in the conceptualization of the model, but also include all the elements of uncertain, subjective and incomplete knowledge in the study domain and assign a value of plausibility (in the form of a Bayesian probability). Probabilistic ontologies then become a sort of uncertain knowledge databases from which it is possible to develop models of probabilistic type, including Bayesian Networks. Ding and Peng (2004) applied a transformation of generic OWL in order to consider the directed acyclic graph of Bayesian Network in the structure of a formal ontology. This allows us to perform automatic reasoning in an ontology with a typical Bayesian Network structure.

2.2 ONTOLOGY AND FUZZY LOGIC

Fuzzy set theory and fuzzy logic were proposed by Zadeh (1965) to manage imprecise and vague knowledge. While in classical set theory elements either belong to a set or not, in fuzzy set theory elements can belong to a set to some degree, according to a membership function. For example, if we consider land use, a particular area belongs to the class "sparse settlement" with a certain degree 0.8, but the same area could belong to the class "agricultural land" with a degree 0.30, while in the crisp logic that area is to be considered either as sparse settlement or agricultural land with a degree 1. Moreover, crisp logic cannot really handle vague values such as the adjectives long, large, thick, far, close, etc. and modifiers such as the adverbs very, quite, almost, etc. These vague or fuzzy concepts can hardly be encoded in a Descriptive Logic Ontology, and unfortunately they look like to be the rule, rather than an exception, in geographical knowledge.

Memberships functions in fuzzy ontology can assume the classic forms like in fuzzy logic: trapezoidal or triangular functions, L-functions, R-functions, linear functions (see Fig. 2).

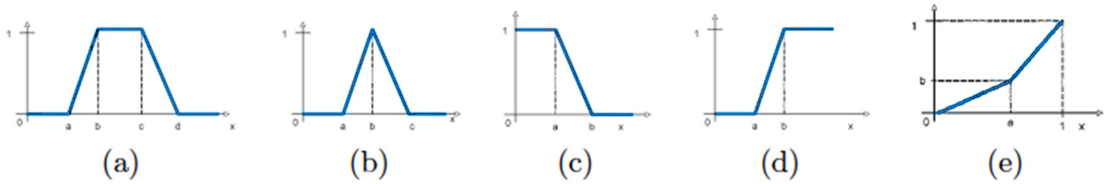

Fig. 2 Fuzzy OWL membership functions: (a) trapezoidal, (b) triangular, (c) L-function, (d) R-function, linear functions

A useful plugin of the formal ontology software Protégé has been developed in order to build fuzzy ontologies. This plugin is named Fuzzy OWL (Bobillo and Straccia, 2010) and it is associated to his fuzzy reasoner named FuzzyDL (Fuzzy Descriptive Logic). The same authors developed also another reasoner named DeLorean (DEscription LOgic REasoner with vAgueNess).

2.3 ONTOLOGY AND POSSIBILISTIC LOGIC

Several approaches have been proposed for dealing with uncertainty or vagueness in knowledge as we have seen above. However a large part of them are based on fuzzy logic, which completely departs from possibilistic logic (Dubois and Prade 1985, Dubois et al. 1994). Fuzzy logic deals with propositions involving vague predicates (or properties) and manipulates truth degrees, whereas possibilistic logic involves certainty and possibility degrees of truth, aiming at the epistemic side of uncertainty (expert subjective knowledge and evaluation of the certainty of this knowledge). The lack of complete certainty about the truth of a considered proposition is to be understood as a consequence of a lack of complete information.

A possibilistic logic proposition is a first order logic proposition with a numerical weight between 0 and 1, which has an upper bound in a possibility measure Π and a lower bound in a necessity measure N (Dubois et al. 1994). The relation between possibility and necessity of a proposition p is given by $\Pi(p) = 1 - N(\neg p)$. Necessity describes the certainty of the possibility measure.

Possibilistic description logics provide a flexible framework for representing and reasoning with ontologies where uncertain and/or inconsistent information exists. Qi et al. (2010) developed a possibilistic reasoner called PossDL (Possibilistic Descriptive Logic) Reasoner based on an evolution of Ontology Web Language. Annotated OWL has the possibility to add possibility and necessity values to relationships among concepts, and PossDL reasoner use a sort of possibilistic network (like in probabilistic ontology we can use Bayesian Networks) in order to infer knowledge.

A simple possibilistic taxonomy is proposed by Loiseau, Boughanem and Prade (2006) on the concept of "accommodation" and its synonymous or close terms (Fig. 3).
In the example in Fig. 3, the words like lodge and inn are only considered as possible synonyms, or as entities that can provide the same services. Nothing can be inferred for the necessity from the possibility degree only, it is always possible, for example, that some lodges are not inns. On the other hand, both necessity and possibility degrees between motel and motor inn are 1. These terms are considered as genuine synonyms.

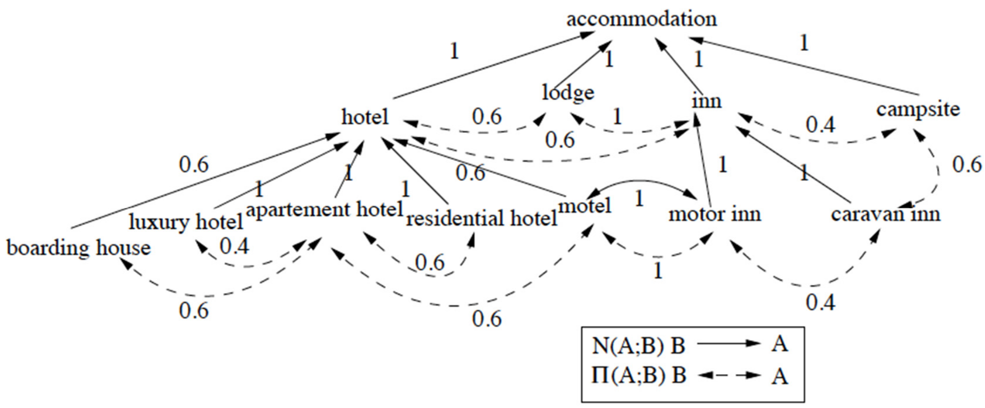

Fig. 3 Possibilistic taxonomy for Accommodation (Loiseau et al., 2006)

3 ONTOLOGY OF UNCERTAIN RELATIONS: AN EXAMPLE

We have seen that different kinds of formal ontologies can encode uncertain knowledge of phenomena and of relationships among phenomena. Through a simple example from the domain of urban geography, we want to show what kind of knowledge could be thus formalized and what are the advantages with respect to more classical crisp ontologies. Through this example, the reader will also better understand the difference between probabilistic and possibilistic formalization of uncertain relations.
After having formally defined the concepts of urban sprawl and of household preference for individual or for collective housing, we want to define a cause-to-effect relationship among the two phenomena.
The classical crisp ontology of this relationship (Fig. 4.a) would formalise a deterministic relationship. Of course, the formal ontology will have to encode in OWL whether the relationship only concerns preference for individual housing causing the true value for urban sprawl, or whether the relationship also foresees that preference for collective housing causes the false value for urban sprawl. These two different causal relationships correspond to two different truth tables for the deterministic relationship, as follows:

Simple causation : Pref. = Ind. Housing → Sprawl = True

	Pref. = Ind. Housing	Pref. = Coll. Housing
Sprawl = True	True	True
Sprawl = False	False	True

Double causation : Pref. = Ind. Housing → Sprawl = True
AND Pref. = Coll. Housing → Sprawl = False

	Pref. = Ind. Housing	Pref. = Coll. Housing
Sprawl = True	True	False
Sprawl = False	False	True

Tab. 1 Truth tables for the deterministic relation "Household Preference causes Urban Sprawl"

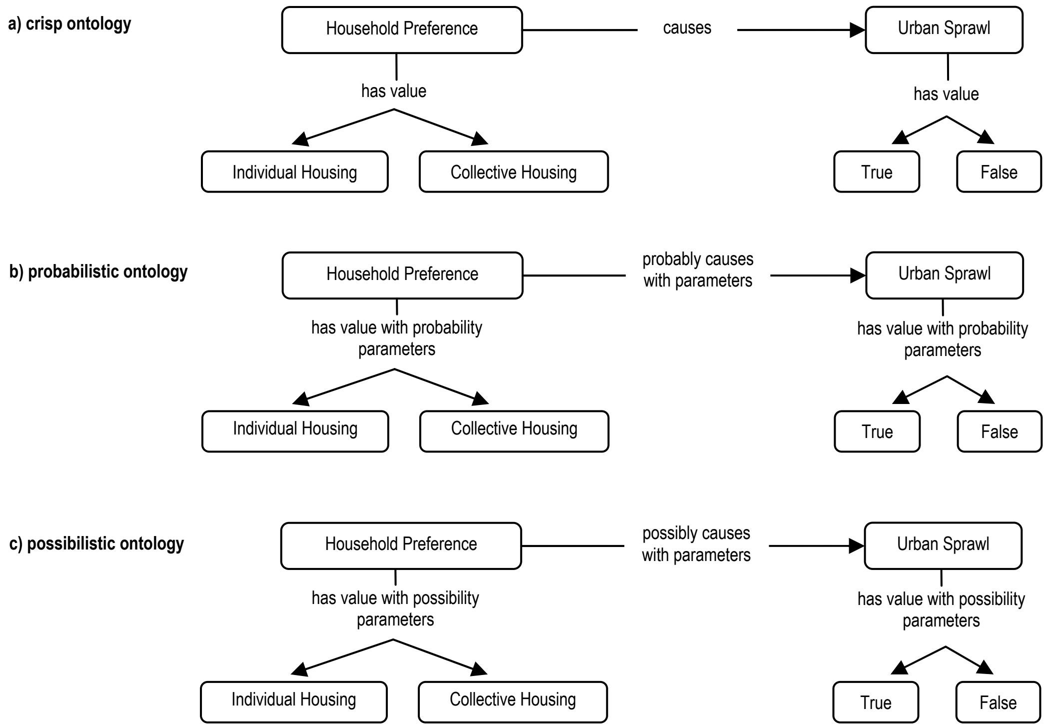

Fig. 4 Different ontologies for the relationship between household preference and urban sprawl

The knowledge encoded in either of these two tables seems to us particularly inappropriate for reasoning about real-world cases of relations between household preferences and urban sprawl, whether this is in the context of diagnostic analysis (did household preferences cause urban sprawl in the case studies?) or in predictive analysis in the context of spatial strategic foresight (will household preferences cause urban sprawl in the case studies?). Reasoners processing this ontology in OWL can only infer whether urban sprawl is true or not, whenever we have certain knowledge of household preference (and even to do this, the ontology has to encode the double causation). But what if we don't have certain knowledge of household preferences? Besides, even if the latter were known with absolute certainty, are we really sure that knowledge of urban sprawl would follow deterministically from it?

A Bayesian probabilistic knowledge of phenomena and relationships among them would naturally prefer a probabilistic ontology, like the one schematized in Fig. 4.b. The PROWL formalism could thus represent the concepts and the relations with the probabilistic parameters which are associated to their knowledge. Knowledge of household preferences would be modeled through a probability of it being "individual housing" and another probability of it being "collective housing", the sum of the two being 1, according to probability axioms. The cause-to-effect relationship of this phenomenon with urban sprawl would be formalized through four probabilistic parameters, making up a conditional probability table. Once again, causation can concern only one or both values of the Household Preference, as follows:

Simple causation : Pref. = Ind. Housing → Sprawl = True

	Pref. = Ind. Housing	Pref. = Coll. Housing
Sprawl = True	0.8	0.5
Sprawl = False	0.2	0.5

Double causation : Pref. = Ind. Housing → Sprawl = True AND Pref. = Coll. Housing → Sprawl = False

	Pref. = Ind. Housing	Pref. = Coll. Housing
Sprawl = True	0.8	0.3
Sprawl = False	0.2	0.7

Tab. 2 Conditional probability tables for the probabilistic relation "Household Preference causes Urban Sprawl with parameters"

Probability values in each column sum to 1, according to probability axioms. The probabilities linking values of cause and effect inform us both on the strength and the uncertainty of the relationship. The conditional probability p(Sprawl=True | Pref.=Ind.Housing) linking preference for individual housing to urban sprawl being true, is thus particularly strong (0.8, i.e. not too far from 1, which corresponds to a deterministic relation). The conditional probability of urban sprawl being false when households prefer individual housing (0.2 in the example) conveys information on the uncertainty of the causal relationship Pref. = Ind. Housing → Sprawl = True. Whether this uncertainty corresponds to an intrinsic variability of the effect of household preferences on urban sprawl (ontic uncertainty) or to our ignorance of other relationships between urban sprawl and phenomena (for example planning bylaws or availability of land for development) which are not in our knowledge base and which are capable of hindering sprawl even in the presence of preference for individual housing (epistemic uncertainty) is, for the moment, secondary to our argumentation.

Knowledge of housing preferences (whether certain or uncertain) and knowledge of the parameters of the conditional probability table, can easily be used by any PROWL reasoner in order to infer probabilistic knowledge on urban sprawl. Let's imagine that "soft" knowledge of household preferences is given by the probability vector [0.9 0.1], corresponding to individual and collective housing, respectively. Matrix multiplication between the conditional probability table (we will use the one of the simple causation) and this vector will give the probability vector [0.77 0.23] for urban sprawl being true or false, respectively. The PROWL reasoner would come to the following conclusion: urban sprawl is most probably true, but the uncertainty of this outcome (probability is still 0.23 for not having urban sprawl) is higher than the one for households preferring individual housing, as uncertainty was increased through the use of the knowledge of un uncertain causal relationship.

Possibilistic knowledge of phenomena and relationships would instead prefer a possibilistic ontology, like the one schematized in Fig. 4.c. Here, knowledge of household preferences would be modeled through possibility measures of it being "individual housing" and of it being "collective housing". The latter corresponds to 1 – N (individual housing), according to possibility theory axioms, and conveys information on the uncertainty of the possibility of preferences being "individual housing". The cause-to-effect relationship of this phenomenon with urban sprawl would be formalized through four possibilistic parameters, making up a conditional possibility table. In the case of simple causation between preference for individual housing and urban sprawl, we would have:

Simple causation : Pref. = Ind. Housing → Sprawl = True

	Pref. = Ind. Housing	Pref. = Coll. Housing
Sprawl = True	Π (Sprawl | Ind.Hous.)	Π (Sprawl | Coll.Hous.)
Sprawl = False	Π (¬Sprawl | Ind.Hous.)	Π (¬Sprawl | Coll.Hous.)

	Pref. = Ind. Housing	Pref. = Coll. Housing
Sprawl = True	1	1
Sprawl = False	0.3	1

Tab. 3 Conditional possibility table for the possibilistic relation "Household Preference causes Urban Sprawl with parameters"

How can we read this table? The first column formalises the simple causation: whenever households preferences go to individual housing, it is wholly possible (possibility = 1) to cause sprawl, but this causal relationship has an uncertainty of 0.3 because this is the value of the possibility of sprawl being false even in the presence of preferences for individual housing. The second column formalises the absence of relation when household preference goes to collective housing (it corresponds to the 0.5 0.5 probabilities of the second column in table 2): both urban sprawl and its absence are wholly possible (and hence completely uncertain) when households prefer collective housing.

A PossDL reasoned could use the knowledge of housing preferences and of the parameters of the conditional possibility table, to infer possibilistic knowledge on urban sprawl. Let's imagine that possibilistic knowledge of household preferences is given by the vector [1 0.2], corresponding to possibilities for individual and collective housing, respectively. Max-min composition rules between the conditional possibility table and this vector will give the possibility vector [1 0.3] for urban sprawl being true or false, respectively. This means that urban sprawl is wholly possible (possibility = 1) but its uncertainty is 0.3. Once again, uncertainty of the conclusion that sprawl is possible is higher than uncertainty of the premise that households prefer individual housing: this is the consequence of the use of a relatively uncertain (possibilistic) causal relation.

4 CONCLUSIONS

Reasoning on uncertain geographic knowledge, formalized through uncertain ontologies, whether probabilistic or possibilistic, is able to convey a coherent uncertainty measure of inferred knowledge. The applications presented in this paper are of course just examples of the modeling potential of uncertain formal ontologies. Domain knowledge encoded in such ontologies can be seen as fragments which could eventually be retrieved in the Semantic Web and combined by modelers (either human or software) and used as building blocks of more complex models: Bayesian probabilistic networks, fuzzy Bayesian networks, possibilistic networks, etc. Costa et al. (2008) thus propose to use PROWL ontologies in order to support the development of multi-entity Bayesian networks.

The problem of an uncertain Semantic Web will eventually be the one of combining uncertain ontologies using different formalisms. Wang et al. (2007) use Dempster-Shafer and possibility theories in order to combine different (and sometimes contradictory) crisp ontologies through appropriate ontology matchers. The indication seems clear: it is through more general uncertainty theories that uncertain ontologies can be combined. Demptster-Shafer and imprecise probabilities theories could thus be used in order to combine crisp, probabilistic, fuzzy and possibilistic ontologies, as they are generalizations of the formal theories underlying these ontologies.

Beyond these methodological perspectives, we believe that the application potential of uncertain ontologies to geographic knowledge is huge. Classical crisp ontologies have already proved of great help in insuring data interoperability among geographic models and applications (like in GIS and web-based GIS). Uncertain ontologies can be the preliminary phase of more complex uncertainty-based models. The advantages of moving to uncertainty-based models is evident: whether it is in the analysis of geographic space or in decision support for planning, reasoning on geographic space is almost always reasoning with uncertain knowledge of geographic phenomena.

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IMAGES SOURCES

Figg. 1, 4: Caglioni and Fusco (2014), University of Nice Sophia Antipolis, UMR7300 ESPACE

Fig. 2: Bobillo and Straccia (2010), Fuzzy OWL plugin for Protégé.

Fig. 3: Loiseau et al. (2006) Evaluation of Term-based Queries using Possibilistic Ontologies.

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