RESEARCH ARTICLE

A Formal Model to Infer Geographic Events from Sensor Observations

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The Sensor Web provides wider access to sensors and their observations via the Web. A key challenge is to infer information about geographic events from these observations. A systematic approach to the representation of domain knowledge is vital when reasoning about events due to heterogeneous observational sources. This paper delivers a formal model capturing the relations between observations and events. The model is exploited with a rule-based mechanism to infer information about events from in-situ observations. The paper also describes how the model's vocabularies are used to formulate spatio-temporal queries. A use case for reasoning about blizzard events based on real time series illustrates the formal model.

Keywords: events, sensor web, ontology, rule-based reasoning, event-oriented queries

1. Introduction

Environmental sensors provide users with an increased understanding of geographic phenomena. For example, river stage sensors aid forecasters in tracking overflow into agricultural fields, satellites and weather stations help weather forecasters to predict hurricane development and movement, and groundwater monitoring systems provide insights into groundwater fluxes and nutrient dynamics. Frank suggests that, "our knowledge of the world follows (only) from observations. [...] processes change observable properties" (Frank 2003). The premise here is that sensors observe certain properties; these values

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can be used to reason about geographic events and their interactions with the environment (Devaraju 2012). Consider the following: when a bush fire develops, it changes surrounding thermo-physical conditions that are indicated by observed properties such as temperature, relative humidity, wind speed and dryness of vegetation. We infer the presence and behavior of a bush fire from these properties and their changes.

1.1. *Motivation*

How can we infer meaningful descriptions of geographic events from observations? This inference is usually carried out by environmental numerical models or spatio-temporal models. Numerical models contain implicit assumptions concerning the occurrence-of-interest, and are limited to domain experts and hard to manipulate, thereby limiting interoperability across different applications (Alexandrov *et al.* 2011). In the geospatial domain, there are numerous spatio-temporal models[1], stemming from snapshot models (Armstrong 1988), object or feature-oriented models representing changes of objects in terms of spatial and attributes (Langran and Chrisman 1988, Langran 1992, Worboys 1994), or event- and process-oriented models (Peuquet and Duan 1995, Worboys 2005, Yuan 2001, Claramunt and Thériault 1995, Worboys and Hornsby 2004). Worboys (2005) identifies the last stage of development as "a full-blooded treatment of changes", in which occurrences, i.e., events, processes or actions are treated as primary modeling entities. According to Yuan, while various event-oriented models have introduced ideas to integrate spatial and temporal data, "the lack of common definitions in terminology and coherent theoretical frameworks presents many challenges to further developments in temporal GIS "(Yuan 2008, p.1147). "In addition to common vocabularies and theoretical frameworks, research is needed in spatiotemporal ontology, representation, reasoning, query analysis [...]" (Yuan 2008, p.1148). Peuquet also emphasized that "semantically-driven representations and query languages are needed that seem 'natural' to the human user, and that at the same time utilize the medium of computing to best advantage"(Peuquet 2001, p.7). Nittel *et al.* also expressed that, "looking at the flood of collected and integrated real-time sensor data, it becomes clear that the cognitive aspects of users must be addressed and that higher-level, semantically rich data representation models and query languages [concerning events] are necessary"(Nittel *et al.* 2008, p.4). The work presented in this paper is comparable to the last stage of development of spatio-temporal models as suggested by Worboys (2005) in terms of its objectives, which are to represent complex events, their participants and the relations between them. However, it differs from the existing event-oriented models in several aspects. First, we use an ontology-based approach to provide common and explicit descriptions of events as well as their sensing information. The sensing concepts are modeled after the OGC's Observations and Measurements (O&M) data model (Cox 2007). Second, the ontological vocabularies are meant to be 'building blocks' for developing application ontologies that support inferences of events from in-situ observations. Third, we have utilized Semantic Web technologies and reasoning mechanisms to interpret observations from various sensors. Finally, meaningful queries concerning events are also supported.

Various ontologies have been developed to classify geographic events, e.g., (Tripathi 2005, Babitski *et al.* 2009, Brodaric and Probst 2009, Raskin *et al.* 2004). Some of these specifications are designed for specific application domains, and only represent events

[1]For the literature on existing spatio-temporal models, see Langran (1989), Peuquet (2001), Pelekis *et al.* (2004), Worboys (2005), Galton (2009), Yuan and Hornsby (2007).

for their applications. They do not offer common vocabularies for representing complex events; consider for example, how a complex event such as a run-off is made of other events like precipitation, interception, and infiltration. Moreover, there is no support for distinguishing participants. For instance, amounts of rainfall are *produced-by* a hurricane and a number of states are *affected-by* the event. In the Semantic Web, event-oriented ontologies (Scherp *et al.* 2009, Schlenoff *et al.* 2000, Shaw *et al.* 2009, Van Hage *et al.* 2011) capture common characteristics of events, including participation and composition relations, spatial and temporal properties. Nevertheless, the event concept is not explicitly associated with sensing concepts such as observation event, sensor and result. A Sensor Web consists of web-accessible sensors where the sensors and their observations can be accessed via a common standard such as the OGC's Sensor Web Enablement framework. Existing formal specifications related to the framework, e.g., Bermudez *et al.* (2006), Probst (2006), Compton *et al.* (2009) primarily represent sensors and observations. They do not capture information concerning events (Broering *et al.* 2009).

As more and more observations are gathered from heterogeneous sources in the Sensor Web, the relations between observations and inferred events should be made explicit in a machine-readable form. Here, constructing an ontology is a promising solution as an ontology can formally capture the knowledge of a domain, while making the domain assumptions explicit (Noy and McGuinness 2001). Further, an ontology supports reasoning, thereby discovering implicit facts about the domain of interest. An ontology-based query expansion is also useful to discover relevant information, as opposed to traditional search queries based on relational constraints (Fu *et al.* 2005, Bhogal *et al.* 2007).

1.2. *Goals and Scope*

What is currently missing is a formal specification that elucidates concepts associated with events that are particularly significant from a sensing viewpoint, and at the same time are designed to reach Sensor Web applications. The goals of the paper are to:

a. Develop an ontology formally representing the relations between geographic events and observations.
b. Exploit the ontological vocabularies with a reasoning and querying mechanism to retrieve events and their sensing information.

The work described in this paper contributes to the research effort towards a generic and formal model of events for the Sensor Web. Unlike existing work (Parent *et al.* 1999) dealing with multiple perspectives of the same geographic phenomena, the Sensing Geographic Occurrences Ontology (SEGO) models events from a sensing point of view. The ontology supports inferences of *institutionalized events* (Reitsma 2005) based on the time-series produced by in-situ sensors. *Institutionalized events* refer to real-world natural events whose definitions are institutionally defined. The ontology is kept at a sufficiently general level as to be widely applicable and in accordance with the standard observational data model (Cox 2007). We leave the technical details of sensors and sensing procedures unspecified and to be supplied by a sensor-specific ontology such as Barnaghi *et al.* (2010), Janowicz and Compton (2010).

The next section specifies related work. Section 3 presents the formal model, and section 4 describes its implementation. Section 5 delivers the application of the model in reasoning about blizzards over hourly time-series. A comparison between our approach and alternative approaches is made in Section 6. Section 7 delivers conclusions.

2. Related Work

Table 1 provides a comparison of several semantic-based approaches to modeling and reasoning about geographic events. The comparison provides insights for the development of our formal model in Section 3. The $\surd$ mark indicates that the listed approach has the specified characteristic.

Criteria	Galton and Mizoguchi (2009)		Yuan (2001, 2009)		Campelo *et al.* (2011)		Claramunt and Thériault (1996)		Grossner (2010)		Scherp *et al.* (2009, 2012)	Shaw *et al.* (2009)	Henson *et al.* (2009), Patni (2011)	Rude and Beard (2012)	Worboys and Hornsby (2004), Worboys (2005)
E=Event ; P=Process	E	P	E	P	E	P	E	P	E	P	E	E	E	E	E
REPRESENTATION															
Event-Process Distinctions															
An occurrence with well-defined temporal bounds, i.e., a beginning and an end.	√		√		√	√			√		√	√	√	√	√
An ongoing open-ended occurrence.		√		√						√					
Emphasis on the whole happening, i.e., an occurrence denotes a summary of what has happened.	√		√				√					√			
Emphasis on mechanisms, i.e., a progression of related phases over time.		√		√				√							
Inter-relations between Occurrences															
A composite event is made of other sub-events.	√								√		√			√	√
A durative event constitutes one or more processes.	√		√				√		√						
A process constitutes one or more events.	√		√		√										
A punctual event is an instantaneous temporal boundary; it is not composed of any process.	√														
Participants															
Involvement of one or more participants in an occurrence	√		√		√		√		√		√	√			√
Characterization of the role of a participant.	√								√		√				√
Space and Time															
The location of occurrences can be asserted to spatial regions or named places.			√				√		√		√	√	√		√
The location of an occurrence is derived from the spatial location of its participants.							√				√				
Occurrences have a direct relation to time.	√		√		√		√		√		√	√	√	√	√
Sensing concepts															
Sensor, sensing event, results, and observed property.													√	√	
APPLICATION															
Characterizing a natural occurrence and its temporal parts.	√		√		√				√		√			√	√
Identifying geographic objects participating in an occurrence.	√		√		√		√		√		√				√
Reasoning about events from observations.			√										√	√	
Occurrence-centric information searching and retrieval.			√								√	√	√		

Table 1.: Representing and reasoning about events from sensor observations.

Events and Processes. A common agreement is that the distinctions between events and processes are established on the basis of their temporal characteristics. Events are described as having built-in terminations beyond which they cannot proceed, while processes are not having any termination. The choice of representing these concepts is also driven by the emphasis of an occurrence (Galton and Mizoguchi 2009, Yuan 2009, Claramunt and Thériault 1996). For example, one can center on events to indicate a summary of what has happened and use processes to describe the progression of the occurrence. Some authors assimilate events to facts. For instance, Shaw *et al.* (2009) considered an event to be a record of history reported by some agent, e.g., a historian or journalist.

Rude and Beard (2012) focused on visualization and exploration of sensor observations and introduced primitive events as units of change of sensing data streams. Grossner (2010) specified *historical-process* as a theory of event relations. In Grossner's terminology, a process is known as *activity*. Any set of one or more *activity* instances given temporal boundaries is an event. Worboys (2005) does not distinguish events from processes, but rather uses the term event to encompass all kinds of occurrences; events in his approach are represented using algebraic approaches. Processes are also considered in the form of actions that result in the changes of a geographic object. For instance, (Hornsby and Egenhofer 2000) presented research on specifying identification-based change, whereas Claramunt and Thériault (1996) defined three types of spatio-temporal processes to specify the evolution of a single entity, the functional relationships between entities, and the evolution of spatial structures. Recent work in this direction includes a logical framework called Reasoning about Geographical Processes Campelo *et al.* (2011). The ontology described in this paper does not rely entirely on the temporal character to distinguish events from processes, but also analyzes these concepts from a sensing perspective. This encourages an ontologically and practically sound representation. Yuan (2009) defined an event as a notable occurrence that takes places when environmental or participants-oriented conditions are met. This aspect is related to institutionalized events (Reitsma 2005), and has been adapted in our ontology (see Section 3.2).

Interrelation between Occurrences. There are several relations that may be defined between events and between events and processes. For example, a complex event is composed of several primitive events; an event may constitute one or more processes or a process may constitute several events. Galton and Mizoguchi (2009), Grossner (2010) suggested the relation between events and processes by looking at the way objects and matter relate. This work goes back at least as far as (Bach 1986) emphasizing an event is *made of* processes as an object is *made of* matter. In the same direction, Worboys and Hornsby (2004) identified symmetries between events and objects, thereby suggesting their relations in terms of taxonomy, composition and functionality. However, there is redundancy between functional relations suggested between events (e.g., a perpetuating event playing a positive role in the continuation of another event) and between events and objects (e.g., perpetrator object). Our model supports both taxonomy and composition relations; the difference is that the functional relations (Section 3.2.2) are modeled only between objects and events due to the ontological commitment. Campelo *et al.* (2011) proposed a process as a 'chunking' of the same type of event (e.g., spatial changes) involving the same participants. While we agree that a process may exist by virtue of a sequence of events, this is not a part of our ontological analysis. The main focus of our approach is to infer information about events from observations produced by sensors that are triggered by related processes occurring in the sensing environment. Although the reasoning is focused on events, the notion of process is needed here to explain how event descriptions are abstracted from the physical world; see Section 3.2.1.

Participants. Neither matter-object nor process-event is ontologically prior to the other. This has been agreed upon by most of the existing approaches, which suggest a common participation relation. What is currently missing is the classification of functional participatory relations (Worboys 2005). Some incorporate 'roles' to distinguish entities participating in an event (Galton and Mizoguchi 2009, Scherp *et al.* 2009). Although 'roles' enable a conceptually sound model, it introduces another level of complexity in terms of ontological representation and implementation (Probst 2007). For simplicity, we do not accept this idea. We introduce several function-based participatory relations and specify how these relations can be used to formulate observational queries (Section 3.2.2).

Spatial and Temporal Information. Events have a direct relation to time. Similar to existing approaches, our formal model includes representation of instants, intervals, and temporal elements. Scherp *et al.* (2009, 2012) suggested that the spatial location of an event is determined by the location of its participants. However, this does not necessarily apply to all sensing applications. For further discussion and the proposed solution, see Section 3.2.7.

Sensing Information. Most approaches lack formal vocabularies to describe how observations are related to a natural event. An exception to this generalization is the O&M-OWL ontology supporting the Semantic Sensor Observation Service (SemSOS) (Henson *et al.* 2009). The ontology classifies real world entities (e.g., *object* and *event*) as instances of *feature-of-interest* (i.e., observation targets). While this is acceptable due a different ontological commitment, the issue here is that the ontology also characterizes an information object (e.g., *coverage*) as a feature-of-interest. As defined by O&M-OWL ontology, "a coverage is a feature that acts as a function to return values from its range for any direct position within its spatiotemporal domain". Probst (2006) has shown that this kind of overly-general notion prevents an ontologically sound representation, and thereby inhibits semantics-based information discovery.

Applications. The existing events-oriented models have been employed in several use cases. Few models have been applied to infer events from actual observations, e.g., Yuan (2001), Rude and Beard (2012), Henson *et al.* (2009), Patni (2011). Yuan (2001) developed a hierarchical framework of events, processes, and states to derive storm events from remotely-sensed layers; the work presented in this paper infers events from multiple sensors producing only point observations. The model proposed by Rude and Beard (2012) indicates the events' spatial progression patterns over a sensed region, but it partially covers sensing information; events and sensing information are represented implicitly. Henson *et al.* (2009), Patni (2011) proposed an ontology-based approach for inferring events in the Sensor Web. This work is the most closely related to the scope of the application of our approach. Therefore, we compare these approaches with our approach in terms of reasoning and querying support in Section 6.

3. An Ontology of Geographic Events for the Sensor Web

Figure 1 presents an overview of the proposed ontology. The ontological contributions are summarized in Section 3.3. Throughout the remainder of this paper, `typewriter` font is used for ontological categories and relations.

3.1. *DOLCE Foundational Ontology*

The foundational *Descriptive Ontology for Linguistic and Cognitive Engineering (DOLCE)* (Masolo *et al.* 2003) is adopted as a starting point for building the ontology. The reason for choosing DOLCE is that it provides most of the general notions under which the domain concepts can be classified. DOLCE is relatively mature in the sense that several ontologies (Brodaric and Probst 2009, Kuhn 2009, Barnaghi *et al.* 2010, Probst 2006) addressing different aspects of geospatial and sensing domains have already been aligned to DOLCE. The top categories of DOLCE are `endurant`, `perdurant`, `quality` and `abstract` (Figure 1). `Endurants` exists as wholes at any time they are present. At different times the same endurant may lose or acquire new parts, e.g., `physical-object` such as lake and forest, and `amount-of-matter` such as sediment and

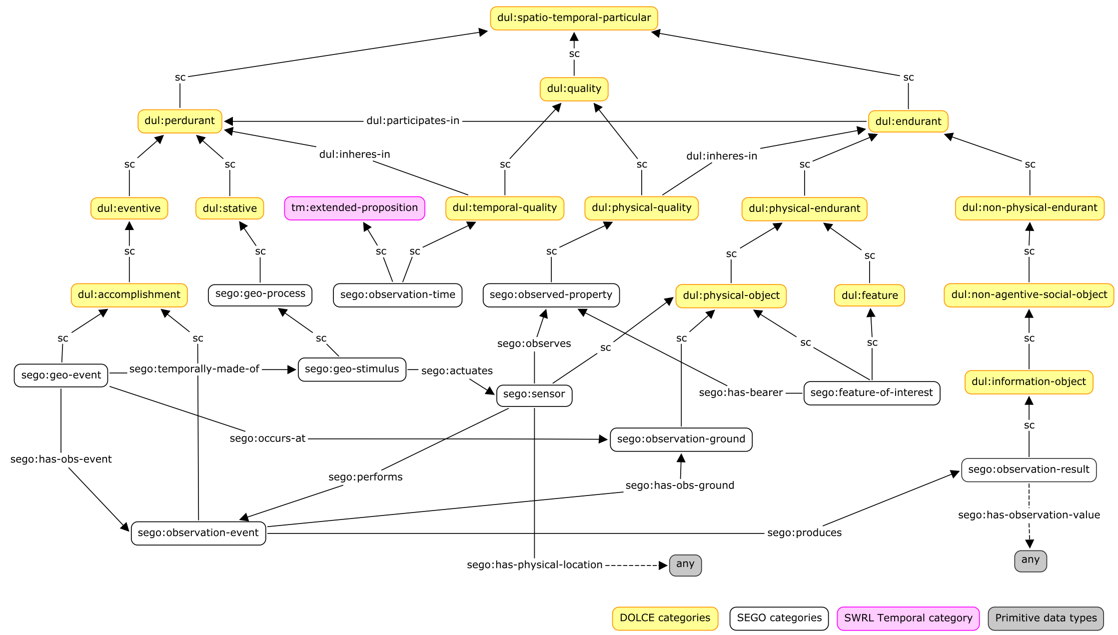

Figure 1.: An overview of SEGO ontology; *sc*, standing for subclass, represents a subsumption relation.

water. `Information-objects` are `non-physical-endurants` (endurants with no mass), e.g., time series and digital images. `Perdurants` extend over time; at any time at which they exist they are only partially present, i.e., `eventive` occurrences such as flash floods and storms, and `stative` occurrences such as raining and infiltration. `Qualities` are temporal or physical properties we perceive or measure, e.g., the water level of a river and the duration of a wildfire. A participation relation holds between an `endurant` and a `perdurant`. A `physical-quality` (including a `spatial-quality`) is `inherent-in` a `physical-endurant`, whereas a `temporal-quality` is `inherent-in` a `perdurant`. For more information on the foundational ontology, see Masolo *et al.* (2003).

3.2. *Ontological Categories and Relations*

The following sub-sections provide descriptions clarifying these ontological questions:

a. What are the key concepts of geographic events and how can they be formally described from a sensing perspective? (Section 3.2.1-3.2.2)
b. What are the sensing concepts required to associate observations to events, and how can they be modeled? (Section 3.2.3-3.3.8)

3.2.1. Processes as Stimuli and Events as Inferred Occurrences

Galton (2006) advocated a theory of event-processes premised on the notion of "experiential and historical" perspectives. As defined by Galton, "The experiential perspective, EXP, relates to the world as we experience it, when it is present. [...] In contrast, the historical perspective, HIST, relates to the *faits accomplis*, the historical record. It is used to describe synoptic overviews that span a succession of instantaneous experiential snapshots" (Galton 2007, p.332). Kuhn proposed the notion of stimulus to link observations to the physical world (Kuhn 2009). He specified that a stimulus can be conceptualized as "a process (periodic or continuous) or an event (intermittent), playing the role of a stimulus when an observer detects it" (Kuhn 2009, p.33). Galton proposed his theory in representing geographic phenomena, but he did not analyze it from a sensor viewpoint. Kuhn suggested a natural occurrence as a stimulus that triggers a sensor, but he did not elaborate further on its representation. We incorporate these two independent positions to describe how events and processes link to a sensing domain. From an observation perspective, geographic processes (`geo-process`) are conceptualized as "experiential" entities. They are ongoing processes (`geo-stimulus`) that actuate a sensor to produce observations. Not all geographic processes are necessarily stimuli. Therefore, `geo-process` subsumes `geo-stimulus`. Geographic events (`geo-event`) are not directly interacting with sensors, but rather they are "historical entities" inferred from observations. The beginning and the end of an event is identified based on certain properties defined by a domain-of-interest. To illustrate, a series of wind speed measurements indicates an ongoing airflow process triggering an anemometer. A high-wind event[2] is inferred by applying a delimiting condition over the time series. A complex example is a combination of processes that actuate a sensor. Consider, for instance, a lysimeter that estimates water loss from a plant-covered soil. The sensor involves water inflow (e.g., irrigation) and water outflow (e.g., water percolation) as its stimuli. DOLCE allows for the possibility that a parthood or a constitution relation can exist between any instances of perdurants (Masolo *et al.* 2003). Our proposal is that a complex event may have other events as its parts (`temporal-sub-event-of`), and each of these sub-events is constituted by (`temporally-made-of`) processes.

3.2.2. Participating Entities

The participants of an inferred event include the `feature-of-interest` observed by a sensor. One way to distinguish participants from one another is by the different roles they play in an event. In lexical semantics, these are known as thematic roles (Sowa 1996, Smith and Grenon 2004). An attempt to classify different kinds of functional participation is presented in a lower module of DOLCE-Lite-Plus (DLP)[3]. However, these relations are restricted to `non-agentive-physical objects` (e.g., social object) and intentional-based types of perdurants (e.g., `activity` and `action`). Therefore, following Sowa, Smith and Grenon (ibid.), we identify several types of participatory relations specializing DOLCE's `participant-in` relation (Table 2).

Participation	**Examples**
Direct and agentive participation	
`performs`, `performed-by`	This is the parent relation of `initiates`, `perpetuates` and `terminates`.
`initiates`, `initiated-by`	Amounts of precipitation *initiate* an infiltration occurrence.
`perpetuates`, `perpetuated-by`	Amounts of sandy soil *perpetuate* an infiltration occurrence.
`terminates`, `terminated-by`	A roadblock *terminates* the flow of traffic on a road.
Indirect and agentive participation	
`facilitates`, `facilitated-by`	A plot of vegetation *facilitates* the rainwater infiltration into the soil.
`hinders`, `hindered-by`	An amount of saturated soil *hinders* quantities of rainwater from infiltrating into the ground.
Primary product	
`produces`, `produced-by`	A snow storm *produces* a huge amount of snow on a specific region.
Secondary product	
`affects`, `affected-by`	The eruptions of Mount Merapi *affected* several settlements.

Table 2.: The functional participatory relations.

3.2.3. Observation Event

Barnaghi *et al.* (2010) classified an `observation-event` as a `situation` (i.e., a social object). Since we want to emphasize actual as well as scheduled sensing activities,

[2] `http://forecast.weather.gov/glossary.php?word=HIGH%20WIND`

[3] The DOLCE Lite (DOL) is the core version of the foundational ontology, whereas DLP contains all the basic extensions (e.g., Descriptions, Places, Time, and Functional Participation) that are plugged to the DOL.

and how they lead to inferences of real events, we classify an `observation-event` as a sub-class of DOLCE's `accomplishment`. The observed properties, results, as well as spatial and temporal details are associated with an observation event, not with a sensor. This has the advantage that one can acquire information about distinct observation events performed by the same sensor. An `observation-event produces` one or more `observation-result`. Following Probst (2006), the `observation-result` is modeled as a sub-class of the DOLCE's `information-object`. A result can range from numerical measurements (e.g., time-series) through categorical measurements (e.g., human weather observations such as mild, windy and rainy) to images (e.g., aerial photographs).

3.2.4. Sensor

OGC's SensorML specification describes sensors as entities capable of observing a property and returning a value (Botts 2007). We model sensors as `physical-object` responding to stimuli. For example, devices (e.g., a wind profiler or a stream gage) and human observers (e.g., citizens supplying data about noise level in their neighbourhood).

3.2.5. Feature-of-Interest (FOI)

The O&M specification allows any entity to be classified as a FOI, such as sensing platforms, regions, artifacts of sampling, events, sample media, and geographic objects (Cox 2007). Probst modeled the `feature-of-interest`[4] as a subcategory of `role` in DOLCE, but did not provide a full account of its representation. It is unclear how a FOI can begin and cease playing a role, a role can be played by multiple entities, and an entity can play multiple roles at the same time. In fact, Probst later acknowledged that "incorporating roles into ontology engineering will yield philosophically sound ontologies at the price of a drastically increased complexity". For simplicity, we treat a `feature-of-interest` as either a `physical-object` (e.g., a lake, a catchment or a volcano) or a `feature`[5] (e.g., a gulf or a cross-section of a river) as defined in DOLCE. Most importantly, a `feature-of-interest` shall be an identifiable entity from an application domain. It can be an object itself (e.g., a river) or a part of the object that can be recognized and observed (e.g., a branch of a river). Amounts seem to be not directly observable as it is difficult to distinguish different portions of matter (Scheider *et al.* 2011). Therefore, we do not regard an `amount-of-matter` as a `feature-of-interest`, but rather as a constituent of a `physical-object`. For example, we can assign a lake (with some water constituents) as the `feature-of-interest` that carries a water salinity property. This practice of assigning indirect hosts as if they were the actual hosts is an essential part of the conceptualization underlying natural language (Probst 2007), and is relevant to retrieving information in a sensing domain.

3.2.6. Observed Property

We regard an `observed-property` as a `physical-quality` that inheres in a FOI. For example, the temperature, the dissolved oxygen and the water level of a water body. We do not consider non-sensorial, abstract properties such as a foreign-exchange rate.

3.2.7. Spatial Information

Some authors (Lombard 1986, Scherp *et al.* 2009) suggested that the spatial location of an event is determined by the sum of the regions of space occupied by its participants. This proposal will run into difficulties when the participants of an event cannot be fully

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[4] Probst (2006) named this category as `entity-of-interest`.
[5] A `feature` is a tangible and "parasitic" entity that is dependent on a `physical-object`.

represented. For example, from a sensing point of view, there is lack of resources with which to describe which amounts of water participated in a stream overflow or which puff of clouds is involved in a precipitation. In some cases, the question of where an event takes place may refer to different aspects of the location of interest. An example of this is the difference between the source location and the run-up location of a tsunami. From an empirical point of view, an event can have a direct spatial location. Nevertheless, it is not possible to model this in DOLCE, as a `spatial-quality` is only `inherent-in` a `physical-endurant`; the spatial location of a perdurant comes indirectly from the spatial location of its participants (Masolo *et al.* 2003). The solution is that we allow the location of an event to be expressed in terms of physical locations (e.g., geo-coordinates) or social conventions (e.g., administrative units).

An `observation-ground` is a `physical-object` where a sensing is assumed to be valid. Its spatial extent is defined empirically, and implies the representative area of an inferred event for a given in-situ sensor. For a ground in-situ observation, the sensor is in contact with the FOI it observes, and deployed on the `observation-ground`, e.g., a weather station. There can be cases where the FOIs are `part-of` an `observation-ground` (e.g., a plot for sampling vegetation) or present near the ground (e.g., a layer of moist air, an aquifer). For the latter, a FOI `covers` an `observation-ground` if it is a `one-sided-specific-constant-dependence` ((Masolo *et al.* 2003, p.31)) on the ground, and is not a part of the ground, e.g., a bush shelter covering the ground. A `feature-of-interest` can be related to an `observation-ground` with spatial relations such as underneath, surroundness, connectivity and containment. This aspect of research has not been fully investigated and requires further exploration. Some of the relations have been specified by Bittner *et al.* (2009), Parent *et al.* (2006).

3.2.8. Temporal Information

Several efforts have been made in the Semantic Web community to develop temporal specifications, e.g., the DAML Ontology of Time[6], the W3C's Time Ontology[7], and the SWRL Temporal Ontology[8]. The `observation-time` specializes the `extended-proposition` defined in the SWRL temporal ontology (O'Connor and Das 2011). We choose the temporal ontology due to its simplicity with considerable expressivity. Further, it offers a set of rule-based built-ins that can be used to reason with temporal information defined using the model.

3.3. *Discussion I: Ontological Representation*

Summarizing, we conceive a sensor as an object that responds to stimuli (e.g., geographic processes), and thereby allows the observation of properties of a particular feature-of-interest. A geographic event is inferred based on standardized rules expressed in terms of observed properties. Its participants include the observed feature-of-interest. The following are several refinements that are applied to DOLCE.

a. In DOLCE, the event-process distinction is mainly based on two linguistic-philosophically derived notions: homeomericity and cumulativity.[9] However, from an

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[6]`http://www.cs.rochester.edu/~ferguson/daml/`
[7]`http://www.w3.org/TR/owl-time/`
[8]`http://swrl.stanford.edu/ontologies/built-ins/3.3/temporal.owl`
[9]An occurrence is cumulative if it holds of the mereological sum of two of its instances, where it is homeomeric if all its temporal parts can be described in the same way used for the whole occurrence.

empirical viewpoint, geographic processes can be conceptualized as homeomeric only up to a certain intrinsic granularity; such a granularity varies across and within sensing applications. A human observer may conceive a snowing process that stops and starts repeatedly as homeomeric, but a sophisticated sensor may observe small breaks in between. Therefore, in the latter case, the process is regarded as anti-homeomeric. We distinguish events from processes (stimuli) by means of their relations to a sensor, and their temporal characteristics to cater theoretical and practical needs.

b. DOLCE allows a parthood relation between any types of perdurants, including processes, events and states. If we follow the principle that the parthood relation can relate only occurrences that share a similar temporal shape, then geographic processes ought not to be specified as *parts* of a geographic event (or vice versa). We specified the relation (i.e., `constituent`) between events and processes in analogy to the way objects and matter relate (Bach 1986).
c. DOLCE also suggests that the spatial location of an occurrence comes indirectly from the location of its participants. However, we have argued in Section 3.2.7 that from an empirical point of view, an event can have its own spatial location. Therefore, we introduce the category `observation-ground` to denote the location where an event is detected. This proposal pertains to in-situ sensors.

Sensing concepts are developed here based on (Cox 2007, Kuhn 2009, Probst 2006, Barnaghi *et al.* 2010) representing observations and sensors. The existing specifications have left a number of open questions. They have been resolved as follows:

a. Kuhn (2009) suggested both events and processes as stimuli triggering a sensor, but he did not fully elaborate on their representation. We represent geographic processes as stimuli that actuate sensors, and geographic events as inferred occurrences. This proposal also clarifies the question addressed by Barnaghi *et al.* (2010) - “The classification of events in DUL is a work in progress. For instance, there is nothing said about how processes differ from other kinds of events. Therefore, the pattern defines a stimulus as a subclass-of DUL:Event”.
b. While a comprehensive specification may describe amounts as `features-of-interest`, we take a pragmatic approach. We model features of interest as something that can be identified wholly, e.g., `physical-object` or `feature` in DOLCE.
c. Several functional relations have been specified to distinguish participants in an event. They are meant to formulate meaningful observational queries (Section 6.2).
d. Barnaghi *et al.* (2010), Janowicz and Compton (2010) used the user-defined relations to link an observation event to a sensor or an observation event to its results, without referring explicitly to the participation relation. Probst (2006) described the relation between an observation event and an instrument via the general participation relation. We refine this with the functional participatory relations. For instance, the `produces` relation indicates the primary product of an `observation-event`, which is an `observation-result`. We specify the `performs` relation to link a `sensor` to its `observation-event` as a sensor is conceptualized as the doer directly controlling an observation event.
e. Figure 2 depicts several relations between sensing categories. Some of these relations are inferred automatically with a rule-based mechanism, thereby eliminating the need to specify them manually. This is described in Section 5.2.

4. System Implementation

Figure 2 illustrates a system architecture which has been implemented using Java and Semantic Web technologies. The *ObservationManager* retrieves and parses timeseries from Climate Data Online[10] and stores them in the observational database. The ontology repository consists of a three-layered ontology, in which a blizzard application ontology specializes SEGO, and SEGO extends DOLCE. The application ontology represents blizzards and their related events with respect to properties observed by weather stations. SEGO[11] is expressed in the Web Ontology Language (OWL-DL). OWL DL has its foundations in description logics. SEGO also incorporates the SWRL temporal ontology to represent temporal information. The *OntologyManager* collates the observation data from the database into a knowledge base. The *EventDetector* supports the *OntologyManager* to infer information about events, their temporal parts and their sensing information from the ontological model. Here, standard and rule-based reasoning are employed. Queries (Table 4) are expressed in SPARQL[12] and executed using the Jena's SPARQL query engine on the Pellet-backed inference model. Inferred events and their sensing details are accessible via the online clients (Figure 3).

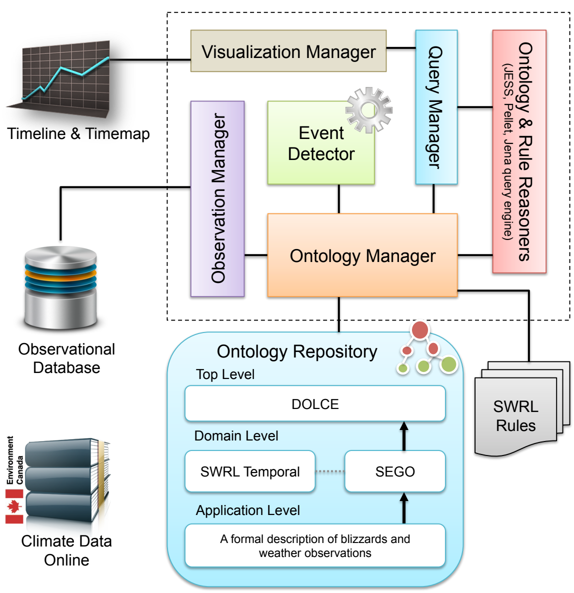

Figure 2.: System architecture.

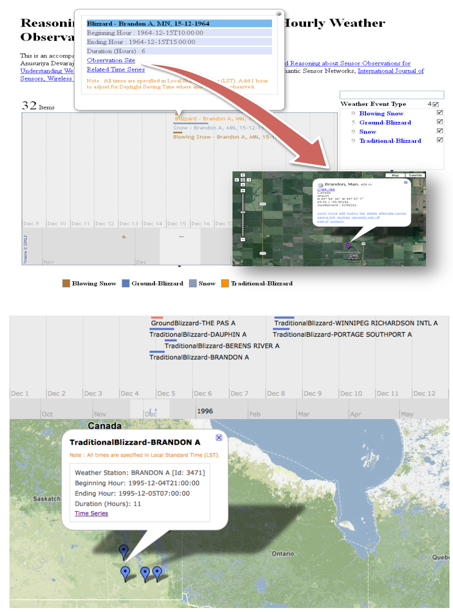

Figure 3.: Events timeline and timemap.

Standard Ontological Reasoning. The standard reasoning is done with the Pellet OWL reasoner[13] to check the logical consistency of the model, deduce new information and update the model with inferred information. A consistency checking ensures that the ontology does not contain any contradictory facts. Consider for example, the domain and range constraints on the `observes` relation: *instance1* `observes` *instance2*. Constraints on the relation restrict that *instance1* must be a `sensor` and the *instance2* must be an `observed-property`. The reasoner will produce an ontological inconsistency error

[10] `http://climate.weatheroffice.gc.ca/climateData/canada_e.html`
[11] http://anusuriya.com/sego/SEGO.htm
[12] SPARQL is a W3C Recommendation. It is a query language for accessing data in the Semantic Web.
[13] `http://clarkparsia.com/pellet/`

if an instance of a `geo-event` is linked to an instance of an `observed-property` with the relation. Similarly, assigning an individual to two disjointed categories (`geo-event` and `geo-process`) will make the ontology inconsistent. Automated classification is also possible on defined categories or relations through the reasoner. Consider the case where we represent that every `observed-property` must have at least one `has-bearer` relation with a particular `feature-of-interest`. This is declared as a *necessary and sufficient condition* for membership in the category `observed-property`. When an individual satisfies such a condition, the reasoner automatically infers that such individual is an instance of the specified category. Another example is when a relation (e.g., `performs`) has an inverse relation (e.g., `performed-by`). By only asserting the first relation, the reasoner will automatically include the latter relation. These examples show the benefits of incorporating an ontology-based approach within the application using an observational database.

Rule-based Reasoning. Some inferences require additional reasoning beyond that supported by the standard reasoning with OWL-DL semantics. Therefore, we employed a rule-based mechanism on top of the ontology. Rules are expressed in terms of ontological vocabularies (Figure 1) using SWRL[14]; see Table 3 for examples of implemented rules. A rule has the form: `antecedent` $\rightarrow$ `consequent`; this indicates that whenever the conditions specified in the antecedent are satisfied, those specified in the consequent must also be satisfied. For reasoning with the rules, we use the Jess[15] inference engine. The SWRL Rule Engine Bridge API supports the translation of OWL and SWRL rules to Jess facts and rules, executing the rules engine, and importing the results back into the ontology. The SWRL temporal built-ins support temporal reasoning, and the SWRL query built-in (`sqwrl:select`) enables rule-based queries.

5. Use Case: Reasoning about Blizzards from Weather Observations

The ontology is evaluated by inferring blizzards from hourly time series supplied by the Meteorological Service of Canada. Definitions for blizzards are varied, according to whether the events occur south or north of the tree line. We use the definition of blizzard applicable to the south of the tree line: (a) wind chill ≥ 1600 Wm^{-2}; (b) mean wind speed $\geq$ 40kmh^{-1}; (c) visibility $\leq$ 1km; (d) presence of blowing snow or falling snow; all the specified conditions (a-d) are expected to last for ≥ 4 hours. A lull period of three hours or less is allowed before a new event is logged (Lawson 2003). A lull period is judged to be a minimal period before a new event is identified. In 2010, Environment Canada changed the definition of a blizzard to harmonize the warnings and criteria across the country.[16] We use the old definition as our approach infers blizzards from the historical data and verifies the results against published event reports.

5.1. *Data Descriptions and Inference Results*

To minimize missing data periods, we use timeseries of consecutive months (Nov-Dec, 1995-1997) from 8 selected stations in Manitoba. For the specified period, a total number of 12 blizzards were inferred, including events that occurred within the same day, between

[14] `http://www.w3.org/Submission/SWRL/`
[15] `http://herzberg.ca.sandia.gov/`
[16] `http://www.theweathernetwork.com/news/storm_watch_stories3&stormfile=what_is_a_blizzardij_010211`

two days and events with lull periods. In addition, different types of weather events (e.g., snow and blowing snow) were also inferred based on timeseries from the Brandon Airport station for the period 1958 to 1995 (see Figure 3). For some stations, wind chill values were occasionally missing and influenced reasoning results. We estimate the missing values with the provided wind speeds and temperates using the Siple-Passel formulae (Siple and Passel 1945) recognized by the weather agency. For all selected stations, the inference results match the number and duration of events as specified in the event reports[17]. A tabular view of the results is also available on the timeline application.

5.2. *Reasoning with Domain and Application-Specific Rules*

Table 3 shows examples of domain and application specific rules related to the application. Variables are marked by question mark prefix (`?x`) and represent the individuals.

	Purpose	Domain Rules
R1	Relate a geographic event to its feature of interest	`geo-event(?g)` ∧ `observation-event(?e)` ∧ `feature-of-interest(?f)` ∧ `has-obs-event(?g,?e)` ∧ `has-foi(?e,?f)` → `participant-in(?f,?g)`
R2	Determine participants of a complex event based on its sub-events	`geo-event(?e1)` ∧ `geo-event(?e2)` ∧ `physical-endurant(?o)` ∧ `participant-in(?o,?e1)` ∧ `temporal-sub-event-of(?e1,?e2)` → `participant-in(?o,?e2)`
R3	Identify the feature of interest of an observation event	`observation-event(?e)` ∧ `observed-property(?p)` ∧ `feature-of-interest(?f)` ∧ `has-obs-property(?e,?p)` ∧ `has-bearer(?p,?f)` → `has-foi(?e,?f)`
R4	Relate a sensor to its observation results	`sensor(?s)` ∧ `observation-event(?e)` ∧ `observation-result(?r)` ∧ `performs(?s,?e)` ∧ `produces(?e,?r)` → `has-obs-result(?s,?r)`
	Purpose	**Application Rules**
R5	Identify a blizzard's sub-events at a given station	`blizzard(?b)` ∧ `blowing-snow(?s)` ∧ `observation-ground(?r)` ∧ `observation-event(?e)` ∧ `occurs-at(?b,?r)` ∧ `occurs-at(?s,?r)` ∧ `has-obs-event(?b,?e)` ∧ `has-obs-event(?s,?e)` ∧ `has-t-quality(?b,?tq1)` ∧ `has-t-quality(?s,?tq2)` ∧ `hasValidTime(?tq1,?tb)` ∧ `hasValidTime(?tq2,?ts)` ∧ `contains(?ts,?tb,temporal:Hours)` → `sqwrl:select(?b,?s,?tb,?r)`
R6	Infer a blizzard's participants	`blizzard(?b)` ∧ `snow-event(?s)` ∧ `physical-endurant(?o)` ∧ `participant-in(?o,?s)` ∧ `temporal-sub-event-of(?s,?b)` → `participant-in(?o,?b)`
R7	Reclassify a general event to a specific type of event	`blizzard(?b)` ∧ `extreme-blowing-snow(?bs)` ∧ `snow-event(?s)` ∧ `temporal-sub-event-of(?bs,?b)` ∧ `temporal-sub-event-of(?s,?b)` → `traditional-blizzard(?b)`
R8	Identify the occurrence of blizzards across neighboring stations.	`weather-station(?s1)` ∧ `weather-station(?s2)` ∧ `neighbour-of(?s1,?s2)` ∧ `has-obs-result(?s1,?r1)` ∧ `has-obs-result(?s2,?r2)` ∧ `performs(?s1,?obs1)` ∧ `performs(?s2,?obs2)` ∧ `blizzard(?b1)` ∧ `blizzard(?b2)` ∧ `has-obs-event(?b1,?obs1)` ∧ `has-obs-event(?b2,?obs2)` ∧ `has-t-quality(?b1, ?tq1)` ∧ `has-t-quality(?b2,?tq2)` ∧ `hasValidTime(?tq1, ?tv1)` ∧ `hasValidTime(?tq2, ?tv2)` ∧ `overlaps(?tv1,?tv2, temporal:Hours)` → `sqwrl:select(?b1,?b2,?s1,?s2?r1,?r2)`

Table 3.: Domain and application-specific rules.

a. R1 automatically links an inferred event to the observation domain with a `feature-of-interest` being the participant of the event. This rule is necessary as

[17]Atmospheric Hazards Northern and Prairie Region, http://pnr.hazards.ca/blizzard.html [accessed 15th December 2011]

descriptions about a feature of interest are usually recorded during an observation event, whereas information about an event is inferred later.

b. R2 implies that if an event is a `temporal-sub-event-of` another, then the participants of the latter include the participants of the former. This rule is generic and can be applied to different types of events. For example, R6 describes how the participants of a blizzard event are inferred on the basis of the participants of its sub-event, at a particular observation site.

c. R3 relates an observation event to its FOI. This kind of rule is useful in case of the information about a feature-of-interest is only available after a scheduled observation is performed. For example, a storm-prone area (a feature-of-interest) that is identified based on a weather radar observing the reflectivity of a catchment.

d. `Observation-event` is the central category holding other sensing categories. The category should be specified in most of the queries retrieving sensing information. To simplify observational queries, R4 infers a direct relation between a sensor and its results based on their relations to the relevant observation events.

e. Various kinds of events can be inferred from the same observations depending on events rules. Co-occurrence relations between these events can be identified via temporal reasoning. Both blowing snow and blizzard events are identified independently. R5 helps inferring the temporal part of a prolonged blowing-snow event corresponding to a blizzard event. Apart from the temporal containment, this rule can also be modified to support other temporal relations such as *contains/during*, *overlaps/overlapped-by* and *equal*.

f. There are two types of blizzards - the `traditional-blizzard` and the `ground-blizzard`. The primary difference is that the latter solely occurs when high winds blow snow that is already present at the surface (NOAA 2009). This means that a ground blizzard does not involve a snowfall event. R7 re-classifies an existing blizzard to a specific type of blizzard.

g. An interesting aspect is to analyze how properties of an event change from one sensor to another neighboring sensor. The weather agency suggests that nearby stations refer to stations within a radius of 25km of a latitude/longitude. In our rule implementation, we use the Haversine formula[18] to find neighboring stations that are within the radius distance of a given station. With this, the selected station is linked to its nearby stations with a symmetric `neighbour-of` relation. Using this relation and a temporal operation, R8 retrieves the occurrence of blizzards across nearby stations. The observed values associated with the blizzards are also included in the reasoning results.

5.3. *Discussion II : Reasoning Support*

Although the use case focuses on a specific type of event (blizzards and related weather events), modeling and reasoning about other geographic events are possible following a similar approach, especially when it comes to institutionalized events and their inferences based on point observations. We have kept the ontology generic enough to be reused for other applications. After all, the aim of using ontology is to ensure its re-usability and extension by an application ontology. Of course, this requires additional application-specific classes and relations to be incorporated into the developed ontology. Since the

[18] `http://www.movable-type.co.uk/scripts/latlong.html`

ontology is available online[19], it can be imported into an ontology-development tool such as Protege to accomplish such a task. Simple rules are embedded in the ontology, whereas complex rules are included in the system implementation. Both can be overridden by applications wishing to modify the rules.

There are several advantages of using rules in our approach. Unlike OWL DL semantics, a complex relation between composed properties is formed via a rule-based mechanism, e.g., R1-R8. These rules are specified in terms of SEGO vocabularies as SWRL has a close association with OWL. Each of these rules represents a distinct separate unit of knowledge that can be added, modified or removed independent of the other rules. For example, R2 is modified to form R6. Both ontologies and rules are embedded in a common logical language; this promotes rules sharing and re-usability. In addition, SWRL features temporal and comparison built-ins that make the rules implementation easier, e.g., R5 and R8.

SWRL has the full power of OWL DL, but at the price of decidability (Motik *et al.* 2005). Decidability means that we can determine whether an argument expressed in the language of the system is valid or not in a finite amount of time. In our implementation, we handle this by DL-safe rules, i.e., a rule-extension of OWL DL and a decidable fragment of SWRL. Practically, this means that the variables in rules are only bound to known individuals, thereby making the rules decidable.

The OWL semantics adopts an *Open-World Assumption (OWA)*, in which the validation is limited, e.g., there is no way to use negation as failure. Similarly, SWRL does not allow non-monotonic negation in the rules. A ground blizzard is a blizzard that does not involve a snowfall event. This definition is inherently *closed world* in the sense that the information is assumed to be complete. Therefore, we identify ground-blizzards by using the SPARQL filter expression *not exists*. This expression supports negation in SPARQL. It can be used to verify the absence of a query pattern in an inferred model.

Another issue is that some rules include additional constructs to the actual individual arguments that need to be considered during the reasoning. The "unwanted" proliferation of rule constructs makes the reasoning cumbersome. For example, R5 and R8 include additional rule expressions as the event's temporal property from SEGO specializes the temporal category in the external ontology.

6. Comparison With A Closely Related Approach

This section compares our approach with the Kno.e.sis Semantic Sensor Web[20] project. The comparison is made with respect to the ontological support for retrieving events and their sensing descriptions. Within the Kno.e.sis project, there are two closely related efforts: (a) A semantically enabled Sensor Observation Service (SemSOS) that introduces an O&M-OWL ontology to support the retrieval of high-level knowledge from low-level observations (Henson *et al.* 2009), and (b) another application implementing the ontology to derive meaningful abstractions from data streams and publishing these as Linked Data (Patni 2011).[21]

The similarity between our ontology and that of SemSOS lies in their covering the basic

[19] http://www.anusuriya.com/sego/SEGOv3.owl
[20] `http://knoesis.org/projects/ssw`
[21] Patni (2011), Patni *et al.* (2011) uses the O&M component of the Sensor and Sensor Network (SSN) ontology prior to the modularisation and alignment of the ontology to DOLCE Ultra Lite. This component of the ontology resembles the SemSOS O&M-OWL ontology.

notions addressed by the OGC's observational model. The differences between the two approaches are in the way the relations between sensing categories, and between observed properties and inferred events are represented. Two aspects covered by the SemSOS ontology that are not fully specified in SEGO are descriptions of sensing methods, and units of measurement. However, in our ontology, the relation between a `sensor` and an `observation-event` is general enough to enable one to extend the respective categories to describe the sensing methods based on Barnaghi *et al.* (2010), Janowicz and Compton (2010). The categories `observation-result` and `observed-property` can be extended with classes from ontologies such as the Measurement Units Ontology (MUO)[22] and the Ontology of Units of Measure (OM)[23].

Query	**O&M-OWL**	**SEGO**
Group A: Asking sensing information.		
(Q1) Specify the location and properties observed by the weather station [station id/name].	●	●
(Q2) What are the observed properties of the [feature-of-interest] and which sensors observe them?	●	●
(Q3) What are the wind speed values and their observed time produced by the [station id/name] on YYYY-MM-DD?	●	●
Group B: Asking information about events and their sensing information.		
(Q4) What are the observed values associated with the blizzard detected by the [station id/name] on YYYY-MM-DD?	◑	●
(Q5) Which station detects more than one blizzard in YYYY and how long do these events last?	◑	●
(Q6) Are there any ground blizzards detected by the [station id/name] between YYYY-MM-DD and YYYY-MM-DD?	N/A	●
(Q7) How do observed values associated with a blizzard occurs on YYYY-MM-DD change from the [station id/name] to its nearby stations?	◑	●
Group C: Asking information about interrelation between events.		
(Q8) Has a snow event occurred during the last HH hours of the blizzard [event id]?	◑	●
(Q9) How long does a blowing snow event last during the blizzard occurred at [observation site] on YYYY-MM-DD?	N/A	●
Group D: Asking information about participants and their roles.		
(Q10) Which atmospheric features have involved in the snow event [event id]?	N/A	●
(Q11) Which atmospheric features have perpetuated the blowing-snow [event id]?	N/A	●
● Full Support ◑ Partial Support ○ Not Supported N/A: Not Applicable		

Table 4.: The comparison of querying support by two ontological approaches.

6.1. *Retrieving Events and Sensing Information*

Previous work (Yuan and McIntosh 2002, Worboys and Hornsby 2004) suggested several classes of queries that reflect information users would like to retrieve from an event-oriented model. Following these suggestions, four groups (Group A-D) of application-specific queries (Table 4) have been designed to compare both approaches. These queries are also similar to scenarios proposed by Henson *et al.* (2009), Patni (2011), including finding sensing information, higher-level events, and temporal relatedness between sequences of weather events. Examples of SPARQL translations of the queries are included in Section 6.2. Note that the queries return results based on the information held in the inferred model. Similar to SQL, they can be easily modified or extended to return other relevant information. In Table 4, *Full Support* means that the specified query can be performed with the vocabularies offered by the respective ontology. *Partial Support* means that some of the vocabularies needed to form the query were missing, or that

[22]`http://idi.fundacionctic.org/muo/muo-vocab.html`
[23]`http://www.wurvoc.org/vocabularies/om-1.6/`

incomplete reasoning or unsatisfactory query results were found. *N/A* indicates that the query is not within the scope of the approach.[24]

6.2. *Discussion III: Querying Support*

This section discusses how the differences in ontological representation and incomplete reasoning mechanisms influence the retrieval of event-driven information.

Group A: Sensing Information: While both approaches can retrieve results from these queries, the difference is that our approach simplifies the query formulation, as not every query expression requires that an observation-event be specified. In the SemSOS ontology, no relation is specified, for example, between a sensor and the properties it observes, or between a sensor and its observation-result. We use rule-based reasoning (e.g., Table 3 (R3, R4)) to automatically infer these relations. Thus, Q1 and Q3 are performed without explicitly specifying an observation-event (see Listing 1).

```
PREFIX sego:<http://data.observedchange.com/sego.owl#>
PREFIX xpth: <http://www.w3.org/2005/xpath-functions#>

SELECT ?sensor ?prop WHERE {
?prop sego:has-bearer ?foi.
?foi sego:has-name ?foiname.
?prop sego:observed-by ?sensor.
FILTER(xpth:contains(str(?foiname), <featureId>))}
```

Listing 1: (Q2) Identify properties and sensors based on a `<featureId>`.

Group B: Events and Observations: These queries retrieve inferred events and their sensing information, e.g., Listing 2. For Q4 and Q5, there are discrepancies between the published event report and the results produced by the alternative approach due to the reasoning mechanism. The blizzard definition implies that an event is identified when its duration is preceded by a time period in which the criteria are no longer satisfied, then a further period that again meets the criteria. Our approach detected a blizzard occurring for 5 hours at Winnipeg Richardson Airport from 7pm to 11pm on 9th January 1997. This matches the event record published by the weather agency. However, with the blizzard observation rule proposed by (Henson *et al.* 2009), five individual events are identified, as it infers a new event at each time instant when the measurements satisfy the event's condition. Our approach also supports more 'realistic' event reasoning as it considers the post-condition of an event (i.e., a lull period) when identifying a new event. For example, a blizzard is detected by our model from the same station on 8th December 1995, from 7am until 8pm. This also matches the event record in the published report. The time period of the event includes a lull interval (8am-9am), as during this interval wind speed measurements do not satisfy the blizzard's definition. However, the alternative approaches failed to consider this in their rule-based mechanism.

To analyze the occurrence of an event beyond a particular station, one should identify nearby stations and a temporal overlapping between inferred events. Q7 is not within to the scope of the alternative research. However, a related aspect is that Patni (2011) uses the GeoNames[25] service to link the location of each weather station to its nearby named location in GeoNames. This allows for the discovery of sensors near a given

[24]The alternative approaches infer events based on the definition specified by NOAA's National Weather Service. Since our implementation uses data from Environment Canada, we modify the rules specified by the approaches to comply with the definition set by the weather agency.
[25]`http://www.geonames.org/`

named location. The same method can be adapted to find nearby stations of a selected station[26]; however, the weather stations in our study area are not fully supported by the service. Our implementation includes complete records of weather stations from the weather agency. Therefore, we use a rule-based query (see Table 3 (R8)) to discover related events across several neighboring stations. The radius determining a nearby station can be overridden by applications wishing to modify the rule.

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX dul:  <http://www.loa-cnr.it/ontologies/DOLCE-Lite.owl#>
PREFIX met: <http://data.observedchange.com/meteo/blizzard.owl#>
PREFIX sego:<http://data.observedchange.com/sego.owl#>
PREFIX time:<http://swrl.stanford.edu/ontologies/built-ins/3.3/temporal.owl#>
PREFIX xpth: <http://www.w3.org/2005/xpath-functions#>

SELECT  ?station ?eventOfInterest ?obsEvent WHERE {
?station rdf:type met:weather-station. ?station sego:performs ?obsEvent.
?eventOfInterest rdf:type met:blizzard. ?eventOfInterest sego:derived-from ?obsEvent.
{
        SELECT ?sensor ?sensingEvent WHERE {
        ?blz sego:derived-from ?sensingEvent.
        ?sensingEvent sego:performed-by ?sensor.
        ?blz dul:has-t-quality ?tq. ?tq time:hasValidTime ?st.
        ?st time:hasStartTime ?stime.
        ?st time:hasFinishTime ?etime.
        FILTER(xpth:substring(str(?stime),1,4)="1997" &&
        xpth:substring(str(?etime),1,4)="1997").
        }
        GROUP BY ?sensor ?sensingEvent HAVING (COUNT (?blz) > 1)
} FILTER (?station=?sensor && ?obsEvent=?sensingEvent) }
```

Listing 2: (Q5) Identify stations that detected more than one blizzard in 1997.

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs:<http://www.w3.org/2000/01/rdf-schema#>
PREFIX dul:  <http://www.loa-cnr.it/ontologies/DOLCE-Lite.owl#>
PREFIX met: <http://data.observedchange.com/meteo/blizzard.owl#>
PREFIX sego:<http://data.observedchange.com/sego.owl#>
PREFIX time:<http://swrl.stanford.edu/ontologies/built-ins/3.3/temporal.owl#>
PREFIX xpth: <http://www.w3.org/2005/xpath-functions#>

SELECT distinct ?blz ?snEvent ?startSnow ?endSnow WHERE {
?blz rdf:type met:blizzard. ?blz sego:occurs-at ?obsReg.
?obsReg rdfs:label ?regName. ?blz dul:has-t-quality ?tqBlz.
?tqBlz time:hasValidTime ?vtBlz.  ?vtBlz time:hasFinishTime ?blzEnd.
?blz sego:has-temporal-sub-event ?snEvent. ?snEvent rdf:type met:snow.
?snEvent dul:has-t-quality ?tqSnow. ?tqSnow time:hasValidTime ?vtSnow.
?vtSnow time:hasStartTime ?startSnow. ?vtSnow time:hasFinishTime ?endSnow.
FILTER (?regName="Brandon Airport" && xpth:substring (str(?blzEnd),1,10)="1995-12-04") }
```

Listing 3: (Q8) Determine the occurrence of snow during a blizzard.

Group C: Interrelation between Events: Patni (2011) uses the "isBefore" relation to represent the order in which the events are detected by the system. While this implies that an event of the same type is detected before another, it is not possible to reason about the temporal relation of different types of events detected by the same sensor or between nearby sensors. In SEGO, the temporal information of inferred events is specified with the SWRL temporal ontology. Therefore, SWRLTemporalBuiltIns can be used in rules to perform temporal operations at a particular granularity, e.g., duration, before, after, overlaps, etc. For example, R5 in Table 3 is implemented to form a parthood relation (`temporal-sub-event`) between events inferred at an observation site. This relation supports Q8 and Q9 (e.g., Listing 3). In our application ontology, the category snow precipitation subsumes different types of snow events, e.g., snow squall and snow flurries. With this subsumption relation, Q8 also considers all individuals that are instances

[26]This service returns the station closest to a given point: api.geonames.org/findNearByWeatherJSON?

of the category snow precipitation. This is an example of the advantages of using an ontology-based search over conventional search in terms of being able to make inferences and matches not available to standard keyword retrieval.

Group D: Event-Object Participation: As we emphasized in Section 3.2.2, more in-depth information about events should also include their participants. Consider observational queries such as, Who *initiated* the Korean War in 1950? Does the bridge *hinder* smolt from emigrating? How much rain was *produced by* the storm? Which US states were *affected* by Hurricane Katrina? In SemSOS ontology, a `feature` can be characterized as an information object (e.g., `coverage`) as well as a real world entity (e.g., `object` and `event`). For the discovery of information sources it is important to know whether the observation is performed on an individual real world entity or on an information object (Probst 2006). Our ontology restricts feature-of-interest to real-world objects on which an observation is performed, and they participate in an inferred event. With this distinction, we can gain understanding about event-object interactions within a sensing environment, e.g., Q10 and Q11. Another advantage of using an ontology-based search is that Q10 is able to retrieve all the features playing different roles in a snow event. The features roles are represented by the functional participatory relations, which are a sub-property of DOLCE's `participant` relation (Table 2). Due to this sub-property assertion, it is inferred that these features are also participants of the event.

In short, SEGO formally captures the descriptions of events, their sub-events, participating entities, and their sensing information. By leveraging these ontological descriptions with reasoning capabilities, meaningful queries over simple observations are supported.

7. Conclusions and Future Work

The contribution of the research lies in the development of SEGO, which constitutes common building blocks for constructing application ontologies that account for inferences of institutionalized events from in-situ observations. The paper has shown how the ontological vocabularies are exploited with reasoning mechanisms to infer information about events and their sensing information. This is particularly useful in the Sensor Web in which observations are often presented in a purely syntactic way, and higher level inferences of events based upon them are missing. The strengths and limitations of the proposed approach have been discussed in terms of representation (Section 3.3), reasoning (Section 5.3) and queries (Section 6.2).

An interesting follow-up is to use SEGO to develop test cases concerning institutionalized events. For instance, in the meteorology domain, weather agencies have published the definitions of weather events in their official glossaries. Future work should also make the location of an inferred event more explicit, through spatial reasoning of representative areas of several stations. Related work in this aspect is representing spatial progression patterns of an inferred event over an observed region (Rude and Beard 2012). We have used time-series produced by an in-situ sensor. It is also possible that a number of events that actually occurred cannot be identified fully, as the weather station might not produce sufficient information, for example, due to the absence of one or more observations related to the event criteria. The use of this approach, combined with concepts representing ground-measured and satellite-derived observations as well as human observations, will be valuable for reasoning about events. The characteristics of similar geographic events may differ considerably and are region-dependent. To illustrate, despite the classification of tropical cyclones being driven from wind strength, they are described differently by the Regional Specialized Meteorological Centres worldwide. A useful extension of the formal model is to communicate these differences to aid global information access. Related approaches in this topic are Parent *et al.* (2006), Brodaric (2008), Scherp *et al.* (2012).

References

Alexandrov, G., *et al.*, 2011. Technical assessment and evaluation of environmental models and software: Letter to the Editor. *Environmental Modelling & Software*, 26 (3), 328–336.

Armstrong, M.P., 1988. Temporality in spatial databases. *Proceedings: GIS/LIS*, 88 (2), 880–889.

Babitski, G., *et al.*, 2009. Ontology-Based Integration of Sensor Web Services in Disaster Management. *In*: K. Janowicz, M. Raubal and S. Levashkin, eds. *Third International Conference of GeoSpatial Semantics (GeoS 2009)*, Vol. 5892 of *Lecture Notes in Computer Science* Springer Berlin / Heidelberg, 103–121.

Bach, E., 1986. The Algebra of Events. *Linguistics and Philosophy*, 9 (1), 5–16 0165-0157.

Barnaghi, P., *et al.*, 2010. *Semantic Sensor Network XG Final Report.* Technical report.

Bermudez, L., Graybeal, J., and Arko, R., 2006. A Marine Platforms Ontology: Experiences and Lessons. *In*: *Semantic Sensor Networks Workshop*, Athens, Georgia, USA.

Bhogal, J., Macfarlane, A., and Smith, P., 2007. A review of ontology based query expansion. *Inf. Process. Manage.*, 43 (4), 866–886.

Bittner, T., Donnelly, M., and Smith, B., 2009. A Spatio-Temporal Ontology for Geographic Information Integration. *International Journal of Geographical Information Science*, 23 (6), 765–798.

Botts, Mike, R.A., 2007. *OpenGIS Sensor Model Language (SensorML) Implementation Specification.* Technical report OGC 07-000, Open Geospatial Consortium.

Brodaric, B., 2008. A Foundational Framework for Structuring Geographical Categories. *In*: *Information Semantics and its Implications for Geographic Analysis (ISGA '08).*

Brodaric, B. and Probst, F., 2009. Enabling Cross-Disciplinary E-Science by Integrating Geoscience Ontologies with Dolce. *IEEE Intelligent Systems*, 24 (1), 66–77.

Broering, A., *et al.*, 2009. Semantic Challenges for Sensor Plug and Play. *In*: J.D. Carswell, A.S. Fotheringham and G. McArdle, eds. *9th International Symposium on Web and Wireless Geographical Information Systems*, Vol. 5886 10.1007/978-3-642-10601-9_6 Springer, 72—86.

Campelo, C.E.C., Bennett, B., and Dimitrova, V., 2011. Identifying geographical processes from time-stamped data. *In*: *Proceedings of the 4th International Conference on GeoSpatial Semantics*, GeoS'11, Brest, France Berlin, Heidelberg: Springer-Verlag, 70–87.

Claramunt, C. and Thériault, M., 1995. Managing Time in GIS An Event-Oriented Approach. Workshops in Computing, *In*: J. Clifford and A. Tuzhilin, eds. *Recent Advances in Temporal Databases.* Springer London, 23–42.

Claramunt, C. and Thériault, M., 1996. Toward semantics for modelling spatio-temporal processes within GIS. *In*: J.M. Kraak and M. Molenaar, eds. *Advances In GIS Research II: Proceedings of the Sixth International Symposium on Spatial Data Handling*, Vol. 1 Taylor and Francis, 47–64.

Compton, M., *et al.*, 2009. A Survey of the Semantic Specification of Sensors. *In*: K. Taylor, A. Ayyagari and D.D. Roure, eds. *2nd International Workshop on Semantic*

Sensor Networks, 8th International Semantic Web Conference (ISWC 2009), Vol. CEUR-WS Vol-522, 17–32.

Cox, S., 2007. *Observations and Measurements Part 1 - Observation Schema.* Opengis implementation standard, Open Geospatial Consortium Inc.

Devaraju, A., 2012. *Representing and Reasoning about Geographic Occurrences in the Sensor Web.* Dissertations in Geographic Information Science (GISDISS) Vol. 7. AKA Verlag ISBN: 9783898386739.

Frank, A.U., 2003. A linguistically justified proposal for a spatio-temporal ontology. *In*: *Workshop on Fundamental Issues in Spatial and Geographical Ontology, Conference on Spatial Information Theory (COSIT 2003)*, Ittingen, Switzerland.

Fu, G., Jones, C.B., and Abdelmoty, A.I., 2005. Ontology-Based spatial query expansion in information retrieval. *In*: *Proceedings of the 2005 OTM Confederated international conference on On the Move to Meaningful Internet Systems: CoopIS, COA, and ODBASE - Volume Part II*, OTM'05, Agia Napa, Cyprus Berlin, Heidelberg: Springer-Verlag, 1466–1482.

Galton, A., 2006. On What Goes On: The Ontology of Processes and Events.. *In*: B. Bennett and C. Fellbaum, eds. *Formal Ontology in Information Systems: Proceedings of the Fourth International Conference (FOIS 2006)*, Vol. 150 of *Frontiers in Artificial Intelligence and Applications* IOS Press, 4–11.

Galton, A., 2007. Experience and History: Processes and their Relation to Events. *Journal of Logic and Computation*, 18 (3), 323–340.

Galton, A., 2009. Processes and Events in Geographic Space. *In*: *Tutorial at COSIT 2009*, Aber Wrac'h, France, 1–37.

Galton, A. and Mizoguchi, R., 2009. The water falls but the waterfall does not fall: New perspectives on objects, processes and events. *Journal of Applied Ontology*, 4 (2), 71–107.

Grossner, K.E., 2010. Representing Historical Knowledge in Geographic Information Systems. Thesis (PhD). Department of Geography, University of California, Santa Barbara.

Henson, C.A., *et al.*, 2009. SemSOS: Semantic Sensor Observation Service. *In*: *Proceedings of the 2009 International Symposium on Collaborative Technologies and Systems (CTS)* IEEE Computer Society, 44–53.

Hornsby, K.S. and Egenhofer, M., 2000. Identity-based change: A foundation for spatio-temporal knowledge representation. *International Journal of Geographic Information Science*, 14 (2), 207–224.

Janowicz, K. and Compton, M., 2010. Sensors. *In*: *The Stimulus-Sensor-Observation Ontology Design Pattern and its Integration into the Semantic Sensor Network Ontology.*, 7–11.

Kuhn, W., 2009. A Functional Ontology of Observation and Measurement. *In*: K. Janowicz, M. Raubal and S. Levashkin, eds. *Third International Conference on Geospatial Semantics (GeoS 2009)*, Vol. 5892 of *Lecture Notes in Computer Science* 10.1007/978-3-642-10436-7_3 Springer, 26–43.

Langran, G., 1989. A review of temporal database research and its use in GIS applications. *International journal of geographical information systems*, 3 (3), 215–232.

Langran, G., 1992. *Time in Geographic Information Systems.* Taylor & Francis.

Langran, G. and Chrisman, N.R., 1988. A Framework For Temporal Geographic Information. *Cartographica The International Journal for Geographic Information and Geovisualization*, 25 (3), 1–14.

Lawson, B.D., 2003. Trends in Blizzards at Selected Locations on the Canadian Prairies.

Natural Hazards, 29 (2), 123–138.

Lombard, L.B., 1986. *Events: A Metaphysical Study.* Routledge & Kegan Paul.

Masolo, C., *et al.*, 2003. *WonderWeb EU Project Deliverable D18: The WonderWeb Library of Foundational Ontologies.* Technical report, Laboratory For Applied Ontology - ISTC-CNR.

Motik, B., Sattler, U., and Studer, R., 2005. Query Answering for OWL-DL with Rules. *Web Semantics: Science, Services and Agents on the World Wide Web*, 3, 41—60.

Nittel, S., Labrinidis, A., and Stefanidis, A., 2008. Introduction to Advances in Geosensor Networks. *In*: S. Nittel, A. Labrinidis and A. Stefanidis, eds. *GeoSensor Networks.*, Vol. 4540 of *Lecture Notes in Computer Science* 10.1007/978-3-540-79996-2_1 Springer Berlin / Heidelberg, 1–6.

NOAA, 2009. National Weather Service Glossary. [online] Accessed: 30 September 2010.

Noy, N.F. and McGuinness, D.L., 2001. *Ontology Development 101: A Guide to Creating Your First Ontology.* Technical report, Stanford Knowledge Systems Laboratory.

O'Connor, M.J. and Das, A.K., 2011. A Method for Representing and Querying Temporal Information in OWL. *In*: H.G. Ana Fred Joaquim Filipe, ed. *Biomedical Engineering Systems and Technologies: Third International Joint Conference, BIOSTEC 2010*, Vol. 127 of *Communications in Computer and Information Science* Springer-Verlag, 97–110.

Parent, C., Spaccapietra, S., and Zimányi, E., 2006. The MurMur Project: Modeling and Querying Multi-representation Spatio-temporal Databases. *Inf. Syst.*, 31 (8), 733–769.

Parent, C., Spaccapietra, S., and Zimányi, E., 1999. Spatio-temporal Conceptual Models: Data Structures + Space + Time. *In*: *Proceedings of the 7th ACM International Symposium on Advances in Geographic Information Systems*, GIS '99, Kansas City, Missouri, USA New York, NY, USA: ACM, 26–33.

Patni, H., *et al.*, 2011. Demonstration: Real-Time Semantic Analysis of Sensor Streams. *In*: K. Taylor, A. Ayyagari and D. De Roure, eds. *Proceedings of the 4th International Workshop on Semantic Sensor Networks 2011 (SSN11)*, 96–99.

Patni, H.K., Real Time Semantic Analysis of Streaming Sensor Data. Electronic thesis or dissertation, Wright State University, 2011. .

Pelekis, N., *et al.*, 2004. Literature review of spatio-temporal database models. *The Knowledge Engineering Review*, 19 (3), 235–274.

Peuquet, D. and Duan, N., 1995. An Event-Based Spatiotemporal Data Model (ESTDM) for Temporal Analysis of Geographical Data. *International Journal of Geographical Information Systems*, 9 (1), 7–24.

Peuquet, D.J., 2001. Making space for time: issues in space-time data representation. *GeoInformatica*, 5, 11–32.

Probst, F., 2006. Ontological Analysis of Observations and Measurements. *In*: M. Raubal, H.J. Miller, A.U. Frank and M.F. Goodchild, eds. *4th International Conference of Geographic Information Science*, Vol. 4197 of *Lecture Notes in Computer Science* Springer, 304–320.

Probst, F., 2007. Semantic Reference Systems for Observations and Measurements. Thesis (PhD). Institute for Geoinformatics, University of Muenster.

Raskin, R., Pan, M., and Mattmann, C., 2004. Enabling semantic interoperability for earth science data. [online].

Reitsma, F., 2005. A New Geographic Process Data Model. Thesis (PhD). University of Maryland, College Park.

Rude, A. and Beard, K., 2012. High-Level Event Detection in Spatially Distributed Time

Series. *In*: N. Xiao, M.P. Kwan, M. Goodchild and S. Shekhar, eds. *Geographic Information Science.*, Vol. 7478 of *Lecture Notes in Computer Science* Springer Berlin / Heidelberg, 160–172.

Scheider, S., *et al.*, 2011. Semantic Referencing of Geosensor Data and Volunteered Geographic Information. *In*: A.P.S. Naveen Ashish, ed. *Geospatial Semantics and the Semantic Web*, Vol. 12 of *Semantic Web And Beyond Computing for Human Experience* Springer, 27–59.

Scherp, A., *et al.*, 2009. F–A model of events based on the foundational ontology DOLCE+DnS ultralight. *In*: *Proceedings of the fifth international conference on Knowledge capture*, K-CAP '09 ACM, 137–144.

Scherp, A., *et al.*, 2012. A core ontology on events for representing occurrences in the real world. *Multimedia Tools and Applications*, 58, 293–331.

Schlenoff, C., *et al.*, 2000. *The Process Specification Language (PSL) Overview and Version 1.0 Specification.* Technical report, National Institute of Standards and Technology.

Shaw, R., Troncy, R., and Hardman, L., 2009. Vol. 5926 of *Lecture Notes in Computer ScienceIn*: *LODE: Linking Open Descriptions of Events.*, 153–167 Springer Berlin / Heidelberg.

Siple, P.A. and Passel, C.F., 1945. Measurements of Dry Atmospheric Cooling in Subfreezing Temperatures. *Proceedings of the American Philosophical Society*, 89 (1), 177—199.

Smith, B. and Grenon, P., 2004. The Cornucopia of Formal-Ontological Relations. *Dialectica*, 58 (3), 279–296.

Sowa, J.F., 1996. Vol. 1115 of *Lecture Notes in Computer ScienceIn*: *Processes and participants.*, 1—22 Springer Berlin / Heidelberg.

Tripathi, A., 2005. Developing a Modular Hydrogeology Ontology Extending the Sweet Ontologies. Thesis (PhD). Department of Geosciences.

Van Hage, W.R., *et al.*, 2011. Design and use of the Simple Event Model (SEM). *Web Semantics Science Services and Agents on the World Wide Web*, 9 (2), 128–136.

Worboys, M.F., 1994. A Unified Model for Spatial and Temporal Information. *Computer Journal*, 37 (1), 36–34.

Worboys, M.F., 2005. Event-oriented approaches to geographic phenomena. *International Journal of Geographical Information Science*, 19 (1), 1–28.

Worboys, M.F. and Hornsby, K., 2004. From Objects to Events: GEM, the Geospatial Event Model. 3234, 327–343.

Yuan, M., 2001. Representing Complex Geographic Phenomena in GIS. *Journal of Cartography and Geographic Information Science*, 28 (2), 83–96.

Yuan, M., 2008. Temporal GIS and Applications. *In*: S. Shekhar and H. Xiong, eds. *Encyclopedia of GIS.* 1 ed. Springer, chap. Processes and Events, 1147–1150.

Yuan, M., 2009. 13. *In*: *Toward Knowledge Discovery about Geographic Dynamics in Spatiotemporal Databases.*, 347–365 CRC Press.

Yuan, M. and Hornsby, K.S., 2007. *Computation and Visualization for Understanding Dynamics in Geographic Domains: A Research Agenda.* CRC Press ISBN-10: 1420060325.

Yuan, M. and McIntosh, J., 2002. A Typology of Spatiotemporal Information Queries. *In*: M.A. K. Shaw R. Ladner, ed. *Mining Spatiotemporal Information Systems.* Kuwer Academic Publishers, 63–82.