Mobile sensor networks for environmental monitoring

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“Ella está en el horizonte -dice Fernando Birri-. Me acerco dos pasos, ella se aleja dos pasos. Camino diez pasos y el horizonte se corre diez pasos más allá. Por mucho que yo camine, nunca la alcanzaré. ¿Para qué sirve la utopía? Para eso sirve: para caminar.”

“Utopia is on the horizon -says Fernando Birri-. I move two steps closer; it moves two steps further away. I walk ten steps and the horizon runs ten steps further away. No matter how far I go, I can never reach it. So what's the point of utopia? The point is this: to keep walking.”

Las palabras andantes – Eduardo Galeano

Contents

Chapter 1

General introduction

1.1. BACKGROUND

1.1.1. Environmental monitoring and sensor networks

Some recent dramatic events have highlighted the important role of environmental monitoring. During the release of radioactive material at Fukushima in Japan in 2011, radiation measurement devices located not only in Japan (Chino *et al.*, 2011) but also all around the world (Masson *et al.*, 2011) helped to monitor the exposure of people, food, water and other environmental resources to radioactivity. Similarly, during the dispersion of the volcanic ash from the Eyjafjallajoekull volcano in Iceland in 2010, remote sensing, in-situ devices and dispersion models were used to monitor and forecast the geographical areas that would be affected by the volcanic plume (Flentje *et al.*, 2010). Moreover, during the oil spill in the Gulf of Mexico in 2010, satellites, aeroplanes, ships, underwater devices and scientists on the ground were deployed to track the spill and determine the magnitude of the environmental damage (GEO, 2010).

Vulnerability to natural disasters and human pressure on natural resources increase the need for environmental monitoring (de Gruijter *et al.*, 2006). Proper responses to emergencies and the rational management of natural resources largely rely on information gathered from environmental observations (de Gruijter *et al.*, 2006). Of the vast variety of environmental observation techniques, remote sensing is one of the most widely used, usually for capturing low-resolution data in large-scale areas and with long scanning periods.

However, when an immediate response is crucial, it may be necessary to rely on constant, real-time and high resolution monitoring of a region of interest (Hefeeda and Bagheri, 2008). For such applications, sensor networks, such as wireless sensor networks (WSNs) (Figure 1.1), are feasible systems for in-situ and real-time monitoring with spatial and temporal resolutions never captured before (Porter *et al.*, 2009; Rundel *et al.*, 2009). They are revolutionising the way environmental data are collected and analysed (Balazinska *et al.*, 2007; Nittel, 2009), their main advantage being the capacity to observe, process and transmit data in a collaborative manner, which produces more value than a single sensor (Liang *et al.*, 2005; van Zyl *et al.*, 2009).

WSNs are made up of a large number of densely deployed sensors in an area very close to a phenomenon of interest. Sensors are autonomous, self-configured, mobile, small, lightweight and low-power devices (Akyildiz *et al.*, 2002; Nittel, 2009). They consist of a processor, memory, a power supply and a radio frequency used to disseminate observed data to users in real time. In addition, a variety of mechanical, thermal, biological, chemical, optical and magnetic sensing devices can be used to observe environmental phenomena (Yick *et al.*, 2008). Applications of WSNs are very diverse, ranging from military target tracking and surveillance (He *et al.*, 2006) to industrial machine monitoring (Gungor and Hancke, 2009) and healthcare and assisted living applications (Wood *et al.*, 2008). In the environmental field, WSNs are successfully used to monitor fire risk (Hefeeda and Bagheri, 2008), earthquakes and volcanoes (Werner-Allen *et al.*, 2006), pollution (Hull *et al.*, 2006), water quality (Jiang *et al.*, 2009), soil moisture (Terzis *et al.*, 2010), animal tracking (Juang *et al.*, 2002) and agricultural productivity (Wark *et al.*, 2007).

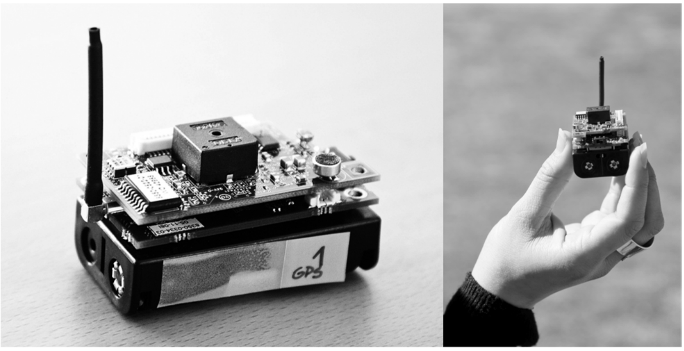

Figure 1.1. A sensor of a wireless sensor network.

Compared with other observation techniques, WSNs have distinct limitations: a limited amount of energy – generally battery power – which restricts the lifetime of the sensor network; a short communication range, which may affect sensor connectivity, with the associated risk of sensor isolations and transition delays; and limited processing and storage capacity in each sensor. In addition, network configurations, especially their topology and connectivity, are highly dynamic because they are mobile and may be damaged (Akyildiz *et al.*, 2002; Yick *et al.*, 2008). Some of these changes are due to internal factors, such as battery drain, sensor movement or a failure in communication. Others may be produced by external factors, such as extreme weather conditions. Additionally, owing to the dynamics of the phenomenon, deployed sensors may not provide proper coverage of the area to be monitored. One of the main challenges in WSN research is to create intelligent and autonomous systems that are aware of these limitations and can adapt themselves.

1.1.2. Mobile sensor networks

Sensor mobility is achieved by attaching sensors to mobile objects such as animals (Juang *et al.*, 2002), people (Campbell *et al.*, 2008), bikes (Eisenman *et al.*, 2007), buses (Zoysa *et al.*, 2007) and robots (Dantu *et al.*, 2005). Sensor mobility can be controlled or uncontrolled. If controlled, the sensors can change their location and trajectories to achieve a certain goal (Jun *et al.*, 2009). For instance, controlled sensor mobility is especially useful to ensure real-time data dissemination by moving sensors where connectivity is broken or where there are isolated sensors (Ekici *et al.*, 2006), to extend the WSN lifetime by moving sensors close to those with low energy levels (Basagni *et al.*, 2008; Jain *et al.*, 2006; Wang *et al.*, 2010), to extend spatial coverage by relocating sensors and avoiding coverage holes (Wang *et al.*, 2009), and to improve monitoring by moving sensors close to events (Butler and Rus, 2003).

In environmental monitoring applications, phenomenon dynamics may mean that deployed sensors no longer provide proper coverage of the phenomenon. In these cases adaptive sampling is needed and the use of mobile WSNs may present advantages. Some of these advantages are evident in examples of environmental emergencies, such as the cases of Fukushima, Eyjafjallajoekull and the Gulf of Mexico mentioned above. To monitor radioactive releases, autonomous mobile sensors in WSNs could be used to track the spread of high radiation levels. They could move very close to the release source and other affected areas to provide real-time observation without human intervention, avoiding exposing people to unhealthy radiation levels. In the case of volcanic ash dispersions, mobile WSNs could move close to critical infrastructure, such as airports. Just a small number of mobile sensors could help to deliver flexible sampling by relocating themselves to locations that will optimise mapping and forecasting of plume dispersions. In the case of oil spills, mobile underwater WSNs may be the only means of obtaining detailed underwater information about the evolution of the oil spill in space and time, especially in areas difficult to access with other types of observation techniques, such as remote sensing. Sampling locations do not need to be defined prior to sampling; in fact, mobile WSNs can determine in real time the best place to move a sensor in response to the evolution of the phenomenon.

1.2. RESEARCH GAPS

Hitherto, sensor network research has primarily focused on software, hardware and sensor configurations (Akyildiz *et al.*, 2002; Nittel, 2009; Yick *et al.*, 2008); monitoring of the environmental phenomenon of interest has received considerably less attention (Zerger *et al.*, 2010). Likewise, most studies on mobile WSNs have focused on addressing the main limitations of WSNs, such as network topology, connectivity and energy conservation (Wang *et al.*, 2010; Younis and Akkaya, 2008). Some work has been done to improve spatial coverage of a study area through sensor mobility (Wang *et al.*, 2009), but this addressed geometric issues of coverage without accounting for the environmental phenomenon itself. The use of mobile sensors as a means to improve the monitoring of environmental phenomena therefore remains largely unexplored. Addressing this requires the consideration of two main mobility aspects.

First, WSNs are highly constrained, which restricts sensor movements. Sensor movements may be constrained by the current state of the sensor network and by the environment itself, for example by low remaining energy levels or because sensors are located in areas difficult to traverse, such as a very dense forest. Some attempts have been made to address mobility constraints (Krause *et al.*, 2009; Verma *et al.*, 2006; Walkowski, 2008; Zou and Chakrabarty, 2007), but they addressed specific mobility constraints without the possibility of extending the approaches to address other constraints. What is missing is a general model for representing mobility constraints arising from both the current status of WSNs and the geographical space where sensors are deployed.

The second fundamental issue to consider is how sampling should be adapted to gain the maximum phenomenon knowledge from each single sensor movement. In other words: where mobile sensors should be moved. Previous studies have addressed this issue by uniformly dispersing sensors across a study area (Howard *et al.*, 2002; Walvoort *et al.*, 2010) and increasing sensor density where events occur frequently (Butler and Rus, 2003) or where a higher monitoring accuracy is needed (Hefeeda and Bagheri, 2008), or moving sensors to minimise the mean kriging error variance (Brus and Heuvelink, 2007; Walkowski, 2008). However, in these studies spatial sampling was adapted to geometric criteria, but not in response to the characteristics of the monitored phenomenon itself. As a result, methods to adapt spatial sampling by mobile WSNs to the characteristics of the monitored phenomenon are still needed.

1.3. OBJECTIVES

This thesis explores approaches to sensor mobility within a wireless sensor network for use in environmental monitoring. To achieve this goal, four sub-objectives were defined:

1. Explore the use of metadata to describe the dynamic status of wireless sensor networks.
2. Develop a mobility constraint model to infer mobile sensor behaviour.
3. Develop a method to adapt spatial sampling using mobile, constrained sensors.
4. Extend the developed adaptive sampling method to monitoring highly dynamic environmental phenomena.

1.4. OUTLINE OF THE DISSERTATION

Chapter 2 explores the use of metadata to describe the dynamic status of wireless sensor networks, which leads to the definition of a context model for WSNs. The model consists of four types of contexts: sensor, networks, sensing and organisation contexts.

Chapter 3 develops a model that describes mobility constraints for the different types of WSN contexts to infer appropriate mobile sensor behaviour. This behaviour is focused on achieving a suitable spatial coverage of the WSN when monitoring forest fire risk.

Chapter 4 develops a spatial sampling strategy for use with mobile sensors. Sensor mobility seeks to maximise the information gained from new observations and minimise the cost-distance of sensor movement under mobility constraints.

Chapter 5 extends the method developed in Chapter 4 for the case of highly dynamic phenomena. It develops an optimisation method for deciding when and where to sample a dynamic phenomenon using mobile sensors. The optimisation criterion is the maximisation of information gained from a new sensor deployment.

Chapter 6 presents the synthesis and recommendations for future research.

Chapter 2

Metadata behind dynamic status of wireless sensor networks

Ballari, D., Wachowicz, M., Manso-Callejo, M. (2009). Metadata behind the interoperability of Wireless Sensor Network. Sensors, 9(5), 3635-3651. (Slightly adapted in order to improve consistency with other chapters)

2.1. INTRODUCTION

Sensors and their networks are becoming essential sources of information for planning, risk management and other scientific applications. They are revolutionising the way geo-referenced data is collected and analysed (Nittel and Stefanidis, 2004). In this paper, the focus is on wireless sensor networks (WSNs). These sensor networks are composed of a large number of sensors, densely deployed within or very close to a phenomenon of interest (Akyildiz *et al.*, 2002). They present an advantage over other sensor networks mainly because the sensors are small, lightweight, and they consume less energy. They are usually self-adaptive systems and can be deployed with a spatial distribution that best fits the communication protocol requirements and the gathering of geo-referenced data (Werner-Allen *et al.*, 2006). Data collected by the sensors are typically transmitted through the wireless network to a sink sensor using radio frequency, which supports the storage of the transmitted data and the communication with other devices and networks.

Interoperability of sensors aims at the achievement of an integrated sensing system, in which sensors act in a collaborative and autonomous approach to produce more value than individual observations (Liang *et al.*, 2005; van Zyl *et al.*, 2009). The objective of the sensor standardisation initiatives, carried out by the Institute of Electrical and Electronics Engineers (IEEE) and the Open Geospatial Consortium (OGC), is to overcome the heterogeneity of devices, communication protocols, networks, data formats and structures. However, in order to support the interoperability of WSNs over time it is necessary to deal with dynamic changes in the network, components and functionalities (De Roure *et al.*, 2005; Grace *et al.*, 2008). In general, interoperability could be achieved by taking into account several levels, including technical, syntactic, semantic, pragmatic, and dynamic ones (Manso *et al.*, 2009). For example: (a) the technical level of interoperability aims at the interconnection of WSNs using common communication protocols, hardware and software; (b) the syntactic level supports the exchange of information among WSNs using a common data structure, language, logic, records and files; (c) the semantic level supports the exchange of information using common vocabularies and it is related to standards and specifications that define schemas for such an exchange. In the case of the pragmatic interoperability level, it allows interconnected WSNs to be known to each other and explore interface applications and services to invoke methods and procedures in order to manage the data they need. Finally, the dynamic interoperability level allows the monitoring of operations of other WSNs and the response to changes.

Currently the OGC Sensor Web Enablement specifications (e.g. SML, SOS, SAS, SPS) provide a set of standards, interfaces and encodings to achieve interoperability of sensor and sensor systems (van Zyl *et al.*, 2009). From our understanding, it is mainly designed to handle the following interoperability levels: technical (web technologies), syntactic (encodings) and pragmatic (standardised interfaces). Moreover, some initiatives are being carried out to deal with the semantic interoperability of sensors (Sheth *et al.*, 2008; W3C, 2009). However, the dynamic interoperability still remains to be addressed in order to monitor and manage changes of status of different WSNs over time. Some of these changes are due to internal factors, such as a battery runs down or a neighbour's communication fails. Others may be produced by external factors such as sensor damage by weather conditions or changes of objectives, purpose, security and privacy constraints.

Therefore, the main research challenge is mostly related to the heterogeneity and dynamic issues of how to maintain interoperability of WSNs over time. When changes of WSN status occur, the systems must respond by triggering self-adaptive processes. These are used to configure, protect, optimise and repair a WSN itself, without the intervention of humans. They monitor the changes, detect failures and performance degradation, begin diagnostic procedures, and conduct preventive, corrective and proactive actions (Ruiz *et al.*, 2004). However, in the case of maintaining dynamic interoperability, the monitoring of these self-adaptive processes is not a simple task. Mainly because the dynamic and unpredictable changes of WSN status cannot be represented using a plain cause-effect approach. For instance, usually if a sensor has a low energy level, the action could be to "sleep" this sensor. But if the sensor is interoperating in an emergency situation (e.g. natural disaster, terrorist attack), then it must continue sensing and transmitting data instead of sleeping. This reasoning process of monitoring and adaptation needs to be contextualised because it depends on the context inside which the sensing is carried out (Giunchiglia, 1993).

Our research premise is the existence of different contexts, both at in-network and data repository levels, which play an important role in the dynamic interoperability of WSNs. From a pragmatic point of view, the dynamic interoperability of WSNs at different periods of time can be maintained by using a set of metadata elements in order to provide the description of observations, processes and functionalities, as well as the current configuration (Di Marzo Serugendo *et al.*, 2007; Dini, 2004; Indulska *et al.*, 2006). Metadata are the common thread that can connect all the status and functionalities of WSNs as well as preserve the context of the sensing data (Dini, 2004; Zhang *et al.*, 2006). This paper describes the development of a context model based on metadata elements for maintaining the dynamic interoperability of WSNs. The reasoning process to contextualise the dynamic interoperability of WSNs using metadata is carried out by two types of reasoning rules. One of them, the contextualising rule, is introduced in the scope of our research to identify WSN status according to different contexts using metadata. The other type, called bridge rules, was previously introduced by Giunchiglia (1993), and it is used to represent the relationships between contexts and the dynamic interoperability. In this paper, however, we mainly focus on contextualising rules. It is important to point out that previous developed context models have mainly considered sensors as a mechanism to capture information about the context itself (Baldauf *et al.*, 2007). In contrast, this paper proposes a model towards a contextualised decision making about how to maintain the sensor dynamic interoperability.

The next section describes the concept of metadata and their principal requirements in the scope of WSNs. Section 2.3 describes the notion of context that has been envisaged. The developed context model and its relevant aspects are discussed in Section 2.4. Furthermore, Section 2.5 describes the reasoning mechanisms of inferring and connecting contexts by providing examples of contextualising rules. Section 2.6 discusses the impact of the context model in WSN interoperability by providing examples of bridge rules. Finally, the main conclusions are summarised in Section 2.7.

2.2. THE NOTION OF METADATA

The most widely used definition of metadata is 'data about data'. They provide the description of the what, where, when, who and how about data (GSDI, 2009). A comprehensive metadata example is that of a photograph, in which metadata describe when and where the photograph was taken, who the photographer was, what is in the photograph, what the camera features are or what post-processes have been done. Metadata are generally used to describe and structure the principal aspects of data with the aim of sharing, reusing and understanding heterogeneous datasets and also allowing information searching and retrieval (Baca, 2008; GSDI, 2009). In the scope of WSNs, metadata have been defined as descriptive data used to depict the WSN, including the environment, the sensors and their status, sensing data, and the WSN as a whole system (Zhang *et al.*, 2006). The use of metadata in WSNs has been mainly related to the execution of routing protocols and in-network data aggregation processes (Heinzelman *et al.*, 1999; Intanagonwiwat *et al.*, 2003; Obashi *et al.*, 2007).

Currently, metadata need to become an explicit part of WSNs in order to preserve the knowledge of the WSN status over time (Table 2.1). On the one hand, they must describe dynamically the changes of status and report them back to other components and systems. For example, if a sensor changes its location or gets damaged, the system must be able to broadcast a message containing metadata elements in order to inform other sensor networks and users about these changes. On the other hand, metadata must be automatically generated and updated, since real-time sensor data require real-time metadata as well. For example, if a sensor fails, the network must automatically (i.e. without human intervention) reconfigure new routes to transmit data. In the same way if a sensor changes its location, the sensing data (and their metadata) must reflect the new location.

Table 2.1 Examples of WSN metadata elements for a sensor measuring temperature.

Data	Metadata Elements (MD)	Value (V)
T = 10	Phenomenon	Temperature
	Data unit	Celsius degree
	Time result	2009/01/23 19:23:45
	Location	Lat 40°26'North; Long 3°42'West
	Feature of interest	Technical University of Madrid
	Sensor type	mts420 crossbow
	Sensor device	Sensirion SHT11
	Other associated data	Humidity, Barometric Pressure, Ambient, Light Sensors, Dual-Axis Accelerometer, GPS location
	Sensor identifier	5
	Number of sensors in network	11
	Number of sensor neighbours	4

2.3. THE NOTION OF CONTEXT

Despite the large amount of research work in the field of Artificial Intelligence, there is no concise definition of a context (Benerecetti *et al.*, 2000). This makes it difficult to select a logical structure of representation and reasoning when context-dependent information is involved, in particular the one generated by WSNs. In this paper, we have used the metaphor of a box as proposed by Giunchiglia and Bouquet (1997). In this case, a context is a box that can be divided into two parts (Figure 2.1):

- inside the box: a collection of WSN status that describes the status of a WSN over time,
- outside the box: a collection of metadata elements (MD) and their respective values (V).

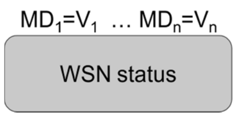

Figure 2.1. The box metaphor of a context.

The assumption is that the content of what is inside the box (i.e. WSN status) is determined by the values of metadata elements associated with that box. In other words, the contexts of WSN status are inferred using metadata elements that describe the sensing system, the current network configuration, and the environmental restrictions. To address the box metaphor into the dynamic interoperability of WSNs, two considerations must be made (Bouquet *et al.*, 2004). First, the dynamic WSN status (and its required self-adaptation) is considered as a local model, in the sense that the WSN status is based on local information. This has to do with the relationship between metadata elements and their values, and the representation of a context inside the box. For example: How do metadata elements and their values affect the representation of a WSN status? In what sense a metadata element provides implicit information which can be used to infer a context? Second, the dynamic interoperability is considered as a global model in the sense that it happens across multiple and heterogeneous WSNs and with multiple and shareable context representations. The issue here has to do with the relationship among the boxes. For example: How do these relationships affect the contents of different boxes? Therefore, the connection between global and local models can only be achieved by the representation and reasoning on different contexts. Contextualising WSN interoperability can be achieved by using reasoning rules, between dynamic interoperability (global model) and the WSN status (local model).

The contexts are local models (where local here implies not shared) that encode a party's view of a domain (Bouquet *et al.*, 2004). In the scope of our research, the parties are the WSNs that interoperate; the domain is the dynamic interoperability and the view of the domain is the current status that has influence over its dynamic interoperability. Thus, in our model contexts are local models that describe the current WSN status in the domain of dynamic interoperability (Figure 2.2).

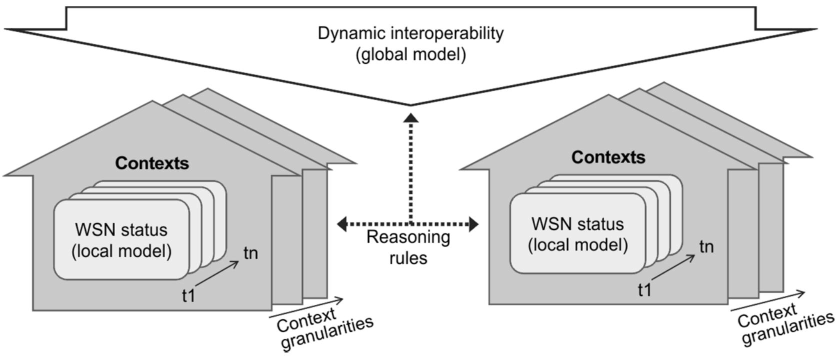

Figure 2.2. Contexts connecting WSN status with dynamic interoperability through reasoning rules.

Bouquet (2004) also points out that the notion of context is best used in those applications where the core problem is the use and management of local and autonomous representations, which is the particular case of WSN applications. Moreover, contexts are easier to define and maintain. They could be constructed with no consensus among different WSNs, or only with a limited consensus which make it possible to achieve the desired level of communication. On the weak side, since contexts are local to WSNs, communication can be achieved only by constructing explicit mapping among the metadata elements of the WSN contexts. In a contextualised WSN, the knowledge is kept locally, but it could be put in relation with the knowledge of other WSN contexts and the global model via explicit mapping. Moreover, the context of a WSN is not unique in the sense that multiple contexts could be inferred for the same WSN status. It could be described with different granularities based on different levels of approximation, perspectives or temporal considerations.

Finally, we distinguish two types of reasoning rules that are involved in the contextualisation of WSN interoperability: (a) Contextualising rules, they are used to infer the contexts of WSN status when WSN metadata and their values are matched by the rules. Following the box metaphor, they allow the interpretation of what is happening inside the box; and (b) Bridge rules that allow the relationships among different boxes in order to connect different WSN status with the dynamic interoperability. They can modify what happens inside a box depending on the inferred contexts in other boxes. However, in this paper we focus on the first of them, contextualising rules, which are showed in more detail in Section 2.5.

2.4. THE DEVELOPED CONTEXT MODEL

The context model describes the current WSN status through describing the sensing functionalities, the sensors, the network and the organisation features. Inspired by the compose-and-conquer approach (Bouquet *et al.*, 2003), we have defined our context model based on four types of contexts. They are: sensing, sensor, network, and organisation contexts. Furthermore, there are relationships among these types of contexts that enable the implementation of contextual reasoning to compose a more understandable and compressible view of WSNs and their dynamic interoperability. Table 2.2 includes some examples of the four types of contexts.

Table 2.2 Examples of the four types of contexts of WSNs.

Sensing Contexts	Sensor Contexts
same/different phenomena mobile phenomena indoor/outdoor	lack of resources immobile/mobile sensor sensor isolation sleep/wake up
Network Contexts	**Organisation Contexts**
low/high sensor density big/small network size exceeded/insufficient coverage area	high/medium/low security restrictions interoperability forbidden administrative area where sensors are deployed

2.4.1. Sensing Contexts

They describe the situation in which data are being captured. They describe the sensing conditions, the sensing operations, the monitored phenomenon, and help to evaluate and understand the sensing data (Campbell *et al.*, 2008). In order to infer these contexts some metadata elements are needed. These metadata elements could contain: (a) spatial information, such as sensors and data locations and spatial reference systems; (b) temporal information, such as instant time or interval of observations; and (c) thematic information, such as features of interests and phenomena (Sheth *et al.*, 2008). Other descriptive metadata elements are related to the captured data, observation processes and data collection characteristics (periodic, continue, or reactive). The inferred contexts could be related to *when* the data are sensing (day, night, season), *where* (sea, mountain, forest), *how* (sensing process, sensors) and *what* (phenomena, feature of interest). For instance, consider a sensor that is attached to a bike and it must monitor only when the bike is moving. When it is inferred that the bike is moving from the GPS or accelerometer data, the monitoring system should be started. In our model, this WSN status in which movements could be inferred from sensing data is represented by a mobile phenomenon context.

2.4.2. Sensor Contexts

They describe individual sensors that compose the WSN. In a field deployment, interoperability happens at sensor level. The individual sensors could participate in collaborative tasks among different WSNs, such as data transmission and in-network data aggregation. The related metadata elements describe the state of memory, communication devices, sensors, actuators, processors and functionalities for each individual sensor. The inferred contexts are in concordance with the sensor status at a specific time and its impact on the interoperability with other sensors. For example, in a mobile WSN in which sensors move freely, communication failure is common if a sensor does not have near sensor neighbours. When the sensor recovers its neighbours, the communication will be recovered too. Interoperability would be interrupted while the sensor is isolated, thus the sensor needs to know its own context and act based on it. In our model this is represented by an isolation context.

2.4.3. Network Contexts

They describe functionalities, collaborations and interrelations among sensors. They describe sensor collaboration tasks in communication and processing functionalities to configure the WSN and its interoperability. The metadata elements used in these contexts are dynamics and some of them could be derived from the sensor contexts as emergent properties of the network. Some context examples are the network composition (homogeneous, heterogeneous), organisation (hierarchical, flat), density (balanced, densely spaced), distribution (regular, irregular), size (small, medium, large), residual network energy and memory (low, high), and spatial coverage area (insufficient, exceeded). In the mobile WSN example, a predetermined study area could be exceeded or insufficiently covered by the mobile sensors. This needs to be known in order to trigger adaptive processes to cover in an efficient way the assigned area. In our model these network status are represented by an exceeded coverage area context and an insufficient coverage area context.

2.4.4. Organisation Contexts

They describe objectives, and legal, security and privacy restrictions. They show policies behind the WSN performance and how it could interoperate with other WSNs or devices. For instance, the interoperability of a WSN may be forbidden for security reasons; or certain sensors could have limitations to interoperate because of restrictions imposed to conserve their energy. Thus if a WSN accesses to an area with a different security code, it must act restricting its interoperability in concordance with the new security level. In our model these organisation status are represented by high, medium and low security level contexts.

2.4.5. Relevant aspects of the Context Model

After analysing the proposed contexts model, we are able to include some of its relevant aspects. They are described as one of the following:

The contexts have different dynamics. The dynamics of changes in the four types of contexts are not the same. The sensor, sensing and network contexts present more dynamic status and these usually are unpredictable. Meanwhile, the organisation contexts are more static, in the sense that their changes are less usual, and they are mainly carried out by a human intervention. The sensing, sensor and network contexts are associated with the network and the environment itself, while the organisation context is associated with non-physical aspects of the WSN.

The contexts depend on the metadata values. The metadata elements characterise the WSN status, or in other words, the WSN status are obtained using metadata. These metadata, however, are not previously assigned to the contexts. Thus, the contexts could change depending on the metadata values. An example is related with the Sensor_Neighbours metadata element (Table 2.3). If the Sensor_Neighbours=12, then the network context is high density of sensors. In this context a sensor could select the best communication path to transmit the sensing data to the sink sensor. Meanwhile, if the Sensor_Neighbours=2, the network context is low density of sensors. Finally if the Sensor_Neighbours=0, the context is isolation and the interoperability could be interrupted. The sensor needs to adapt itself in order to overcome this status and avoid losing sensing data.

Table 2.3 Example of contexts depending on metadata values.

Metadata Element	Values	Contexts
Sensor_Neighbours	12	high density
	2	low density
	0	isolation

The contexts depend on the level of approximation. As an example, we use an essential context component: the location or *where*. The meaning of *where* could change according to the level of approximation (Table 2.4). If a sensor has a GPS device, it is possible to attach the spatial coordinates to sensor measures such as temperature, light or humidity. This spatial location belongs to the sensing contexts. On the other hand, if the GPS device tracks the sensor trajectory, the observed location becomes part of the sensor contexts. Based on the individual sensor locations, it could be possible to define the network coverage area, the extension, density, sensor neighbours, sensor encounters, and detention areas which belong to the network contexts.

Table 2.4 Example of contexts according to different levels of approximation.

Metadata Element	Level of Approximation	Contexts
Location Lat 40°26'North Long 3°42'West	Data location	Sensing Context
	Sensor location	Sensor Context
	Network coverage area	Network Context
	Administrative area	Organisation Context

The contexts have relationships among them. Context relationships are based on bridge rules. They link different contexts when the inference in one context has an influence in another context (Giunchiglia, 1993). The bridge rules allow the mapping of multiple WSN contexts (Bouquet *et al.*, 2003). For instance, to compute the network coverage area (network context) is necessary to know the location of sensors (sensor context). On the other hand, for security reasons only authorised systems (organisation context) are allowed to use certain sensing functionalities (sensing context). The immobile/mobile contexts (sensor context) could be inferred from the GPS or accelerometer data (sensing context). Furthermore, sensor interactions must be validated by security and privacy restrictions (organisation context).

Run-time and historic contexts. From a temporal consideration, we could distinguish two types of contexts, the run-time and the historic contexts. The run-time context is the context of the current WSN status, and it is used in real time. Meanwhile, the historic context is the *memory* of previous status. As an example, in an isolation context the system triggers in-sensor storage processes to avoid losing the sensing data while the sensor remains in this isolation context. When the neighbour communication is restored, a new context is inferred: in-network sensor. However, the sensor needs to have *memory* to know what data were stored within the sensor during the previous context (isolation context) to could transmit them to the sink sensor. Additionally, the sensing contexts use the historic context to preserve the contents of the sensing data.

2.5. REASONING ABOUT WSN CONTEXTS: THE IMPLEMENTATION OF CONTEXTUALISING RULES

Different forms of contextual reasoning are involved to carry out the reasoning mechanisms of inferring and connecting contexts. Benerecetti *et al.* (2000), in their work about the foundation of a contextual reasoning theory, identify three fundamental dimensions of contexts (partiality, approximation and perspective) and their relations with three forms of contextual reasoning (localised, push and pop and shifting reasoning). Thus depending on the context dimension different mechanisms of context reasoning are used.

If the focus is on the partiality context dimension, the reasoning mechanism is localised reasoning. The partiality is the portion of a domain that is represented, and then the localised reasoning does not consider all that is known about a domain, but rather a subset (Benerecetti *et al.*, 2000; Giunchiglia, 1993). In this approach, the reasoning is kept locally based on the local WSN status, and it is linked with other WSN status and with the dynamic interoperability (global model) using the bridge rules. For instance, if the local context of a sensor is a low energy level, the consequence could be to sleep the sensor. But if this context is connected with an emergency context, then the sensor must continue sensing instead of sleeping. This example shows how the inference process in the dynamic interoperability domain could lead to different decisions depending on the local and global models.

Moreover, when the contexts depend on the level of approximation it is possible to change the contexts granularity by adding (pushing) or extracting (popping) some metadata elements into the context box. For instance the *where* context could change according if the approximation is at sensing, sensor, network, or organisation contexts. Then, adding sensor location contexts (individual sensor locations) will determine the network location context (network coverage area). Thus, if the focus is on the degree of approximation, the reasoning about WSN contexts will be push and pop reasoning.

Finally, if the focus is on changing metadata values (perspective dimension) the reasoning about WSN contexts will be a shifting reasoning. This form of reasoning is called shifting because the changes of metadata values shift the WSN contexts. For instance, when the Sensor_Neighbours metadata changes its value from 12 neighbours to 0 neighbours, the perspective from which the WSN is observed also changes from a high density context to an isolation context.

In our approach the WSN contexts are inferred from the WSN status using metadata elements. Therefore, we introduce contextualising rules to reason over WSN status using data and metadata that describe the sensing system, the current network configuration, and the environment restrictions. The contextualising rules are deductive rules (*if-then-else*) and are fed by the current WSN metadata. Some of these metadata are static and established by default (e.g. access restrictions, security levels, and owners). Meanwhile, others are dynamic and automatically extracted from the WSN (e.g. energy level, sensor location). The dynamics of a WSN status should be automatically captured and self-described through metadata and some of them can be derived by the data itself (e.g. the accelerometer data help to infer if the node is moving or fixing).

The implementation of the contextualising rules has been done with Jess rule engine. Jess is a rule-based system that uses rules to derive conclusions from premises. The premises are the *if* first part of rules, meanwhile the conclusions are the *then* second part of rules. The Jess architecture consists of (a) the rule base that contains all the defined rules; (b) the working memory that is the WSN metadata elements and their values (also called facts) that the rule engine operates on; and (c) the inference engine that controls the process of firing the rules and matching them with the working memory. We have used the Jess rule engine integrated into the Protégé knowledge-engineering framework, through the JessTab plug-in (Eriksson, 2003; Friedman-Hill, 2003). This has allowed us to develop the mapping between the Protégé knowledge bases (context classes) and Jess facts (metadata elements and their values). In our implementation, when a new set of metadata instances is uploaded in Protégé, the contextualising rules are executed and, as a result, the current contexts are inferred according to the current metadata values.

In the next section, we show some examples of contextualising rules expressed in Jess language. In these examples contexts are inferred and the interoperability entails to be adapted in order to continue interoperating. Although they are simple rules constructions, they are useful to illustrate how contexts could be inferred from: the automated extracted metadata (Example 1), the sensing data (Example 2) and the metadata extracted using the GPS device (Example 3).

2.5.1. Example 1

This rule uses the battery level to infer whether the sensor is sensing in a low battery context. It is a useful context in WSNs to adapt resource consumption depending on, for example, if the sensor must sleep, or on the other hand, it must continue sensing because the context of interoperability is an emergency situation. The Jess rule engine evaluates the metadata loaded into its working memory. When they match the premise "if the battery level is less or equal than a defined threshold (<= ?battery threshold)", the sensor is classified into the low battery context.

```
(defrule sensor_context::low_battery
(object (is-a metadata) (sensorid ?sensorid) (result_time ?result_time)
(battery ?battery&:(<= ?battery threshold)))
=> (make-instance of low_battery (sensorid ? sensorid) (result_time
?result_time)))
```
(2.1)

2.5.2. Example 2

In this example, contextualising rules are developed to infer whether the context of a sensor is immobile or mobile. In this case, the immobile and mobile contexts are defined using the accelerometer sensing data. When the accelx and accely data match a defined threshold value, the rules classify the sensor into immobile or mobile contexts. Additionally, an extra rule is fired to validate that there are not duplicated instances.

```
(defrule sensor_context::immobile
(object (is-a sensing_data) (sensorid ? sensorid) (result_time ?result_time)
(accely ?accely&:(and (>= ?accely threshold) (<= ?accely threshold)))
(accelx ?accelx&:(and (>= ?accelx threshold) (<= ?accelx threshold))))
=> (make-instance of immobile_context (sensorid ? sensorid) (result_time
?result_time)
(accely ?accely) (accelx ?accelx)))
```
(2.2)

```
(defrule sensor_context::mobile
(or (and (object (is-a sensing_data) (sensorid ? sensorid) (result_time
?result_time)
(accely ?accely&:(or (< ?accely threshold) (> ?accely threshold))) (accelx
?accelx)))
(and (object (is-a sensing_data) (sensorid ? sensorid) (result_time ?result_time)
(accely ?accely) (accelx ?accelx&:(or (< ?accelx threshold) (> ?accelx
threshold))))))
=> (make-instance of mobile_context (sensorid ? sensorid) (result_time
?result_time)
(accely ?accely) (accelx ?accelx)))
```
(2.3)

(mapclass mobile_context)
(defrule remove_if_duplicate_instances_mobile_contex
(object (is-a mobile_context) (sensorid ? sensorid) (result_time ?result_time)
(object ?instance))(object (is-a mobile_context) (sensorid ? sensorid)(result_time
?result_time) (object ~?instance)) => (unmake-instance ?instance)) (2.4)

2.5.3. Example 3

In order to infer if a sensor is sensing in a high or low security geographical area, we used sensors with GPS devices. When the sensors access into an area with a different security level, they must act restricting its interoperability according to the new security level. In practice, GPS sensing data were converted into a spatial database using the PostGIS spatial extension of the PostgreSQL object-relational database. PostGIS allows GIS (Geographic Information Systems) objects to be stored in the database and includes functions for the analysis and processing of spatial objects, such us proximity, adjacency or containment (PostGIS, 2007). Thus, the metadata provide information about where the sensors are located, and whether they are contained in high or low security areas. When these spatial metadata have been calculated, the rule engine is fired and the high security and low security contexts are inferred.

defrule organisation_context::high_security_area
(object (is-a metadata) (sensorid ? sensorid) (result_time ?result_time)
(high_security_area TRUE))=> (make-instance of high_security_context (sensorid
? sensorid) (result_time ?result_time))) (2.5)

(defrule organisation_context::low_security_area
(object (is-a metadata) (sensorid ? sensorid) (result_time ?result_time)
(low_security_area TRUE))=> (make-instance of low_security_context (sensorid ?
sensorid) (result_time ?result_time))) (2.6)

2.6. THE IMPACT OF THE CONTEXT MODEL IN WSN INTEROPERABILITY

In this paper we have mainly focused on the definition of a local context model based on metadata elements. It is still necessary, however, to address the development of a global model for achieving the dynamic interoperability of WSNs. Our proposed local model addresses issues such as sensor mobility, energy levels, sensor isolation, network configurations, the entrance and exit of sensors within security areas and privacy and security constrains. We argue that based on the WSN inferred contexts it is possible to maintain the dynamic interoperability when unpredictable changes of status occur. In other words, the WSNs could be monitored themselves and when a certain status is detected, the current contexts and their responses are inferred at the local model as well as at the global model. This is carried out based on the description of WSN contexts over time that allows making more intelligent decisions based not only on the location and technical specifications of sensors, but also on the purpose of interoperability, security and privacy constraints, the environment in which the sensing and interoperability take place and the current status of network.

In fact, the contexts describe what happens in the WSN and in its surroundings; meanwhile, the bridge rules provide the reasoning mechanism that relates the contexts of different WSNs. At the global model, decision making could take place in order to decide what should be done to continue interoperating in despite of the dynamic changes. Once the local contexts are inferred, they could be linked using bridge rules. For example, the interoperability is established in a geographic area of interest for solar luminosity monitoring. Then, when a mobile sensor with a light measuring device enters in this area, it begins to sense and transmit measurements (Figure 2.3a). However, if the sensor density is low, the sensing data could not be transmitted in real time due the insufficient number of sensors. Thus, it is needed to interoperate with other sensors and use them as intermediate sensors to transmit the sensing data in real time, evaluating previously if their battery levels are high (Figure 2.3b).

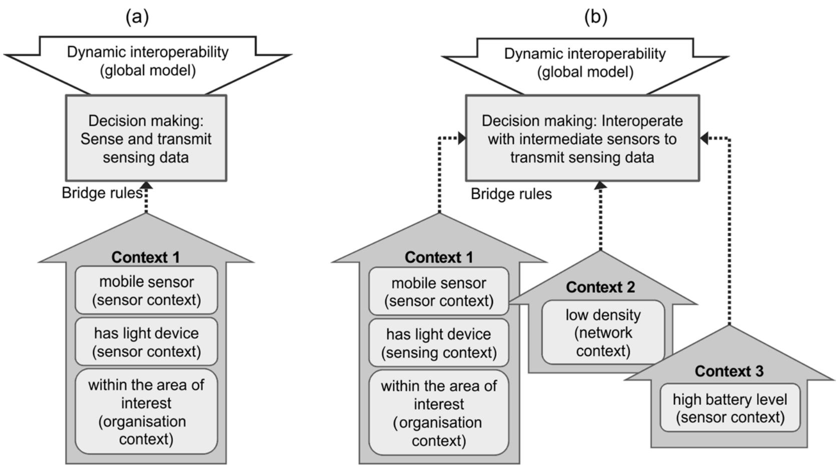

Figure 2.3. (a) Bridge rules evaluating local contexts. (b) Bridge rules linking and evaluating multiple contexts.

The use of contexts in sensor interoperability tends towards an adaptive interoperability. For example, a sensor begins to interoperate with other sensors and its energy context is high. Later it becomes low and the interoperability could be interrupted. However, if the purpose of interoperability is an emergency situation (i.e. hurricane, flood, fire) the sensor could continue sensing. Other example with different interoperability purpose is a WSN transported by people in which the sensors interoperate to exchange some parameters whether people interact. The criteria of these reasoning processes based on multiples local contexts and global interoperability purpose need to be defined in future research.

2.7. CONCLUSIONS

In order to handle changes of WSN status and to support dynamic interoperability, the relationships between local and global interoperability models entails to be addressed. Towards this challenge, we have introduced the notion of contexts as an explicit representation of WSNs status inferred from metadata elements. Moreover, a context model is proposed to describe the WSNs status based on four types of contexts: sensing, sensor, network and organisation contexts. The focus has been on describing and reasoning over different contexts, using two types of reasoning rules: contextualising rules and bridge rules. In this paper we have mainly focused on the development of contextualising rules as a mechanism to infer different WSN contexts using metadata elements. As a proof of concept, we have shown examples of contextualising rules based on the localised reasoning in the sensor and organisation contexts, as well as the shifting reasoning in which the contexts depend on the metadata values.

We have shown the important role of metadata elements to contextualise the dynamic interoperability of WSNs. The metadata act as parameters in order to interpret what is happening inside the different contexts. Depending on their value and the level of approximation, the interpretation of contexts could be different. Some people may argue that metadata are low level information about WSNs, but managing them in a properly form (contextualising rules), they allow the inference of high level of knowledge about the WSN contexts in which the sensing is carried out. The use of spatial metadata, such as location, coverage area or security area, adds the spatial dimension into the reasoning process allowing the inference of spatially related contexts.

Furthermore from a sensing data collection view point, sensor networks are capturing a massive amount of data and with their interoperability such an amount increases even more. Currently, all these data are provided in isolation without any context (van Zyl *et al.*, 2009). Thus, contextualising the interoperability would allow a more intelligent recovery of the sensing data and available resources based not only in queries about where (geographic coordinates), when (date and time), how (sensor specification) or what (phenomenon type), but also related with more rich contextual information such as: sensors that are sensing in a high security areas or near the sea; sensors that are sensing within the same context but not necessary in the same geographical area, the context in which sensors had been interacted, or all the sensors that are allowed to interoperate and that also are attached to public transport. The context-based information retrieval could be pointed out as an important issue of Sensor Web.

This paper describes our first step towards the maintenance of WSN interoperability. In order to contextualise the WSN interoperability further analysis on the relationships among contexts is needed to develop a representation and bridge rules of the global model (dynamic interoperability). Therefore, further research should be done to implement bridge rules as part of a decision-making process that can allow the reasoning among different contexts and the dynamic interoperability, which in turn could allow decisions about what should be done to maintain the dynamic interoperability in despite of the changes of WSN status. We are planning to explore more in detail the localised, push and pop and shifting reasoning tasks and their relation with the bridge rules. Finally, we will implement a concrete case of study for the evaluation of our context model as an approach to address the dynamic interoperability of WSNs.

Chapter 3

A mobility constraint model to infer sensor behaviour in forest fire risk monitoring

Ballari, D., Wachowicz, M., Bregt, A. K., Manso-Callejo, M. (2012). A mobility constraint model to infer sensor behaviour in forest fire risk monitoring. Computers, Environment and Urban Systems. 36, 81-95.

3.1. INTRODUCTION

Forest fire risk monitoring is a critical fire prevention activity to minimise environmental as well as human damage. It characterises when and where a forest fire is more prone to occur (Chuvieco *et al.*, 2010; Dlamini, 2010). Remote sensing techniques are broadly used to capture low resolution data in large-scale areas and with long scanning periods. However, if an immediate response is crucial, it becomes necessary to provide constant, real-time monitoring of a region of interest (Hefeeda and Bagheri, 2008). Within this scope wireless sensor networks (WSNs) have been proved to be feasible systems to enable real-time monitoring of areas never overseen before, with spatial and temporal resolutions never captured before (Porter *et al.*, 2009). Therefore, WSNs have been successfully used not only to monitor fire risk for early detection (Hefeeda and Bagheri, 2008; Son *et al.*, 2006), but also to detect already started fires (Doolin and Sitar, 2005; Yu *et al.*, 2005), and to monitor their behaviour (Antoine-Santoni *et al.*, 2009; Hartung *et al.*, 2006).

WSNs are made up of a large number of geographically and densely deployed sensors very close to a phenomenon of interest. The sensors are self-configured, mobile, small and lightweight. They disseminate sensing data to users in real time using a radio frequency (Akyildiz *et al.*, 2002; Nittel, 2009). Mobility is achieved by attaching the sensors to mobile objects such as animals (Juang *et al.*, 2002), people (Campbell *et al.*, 2008), bikes (Eisenman *et al.*, 2007), vehicles (Zoysa *et al.*, 2007) and robots (Dantu *et al.*, 2005). Furthermore, sensor mobility can be controlled or uncontrolled. If controlled, the sensors by themselves can change their location and trajectories to achieve a certain goal (Jun *et al.*, 2009). For instance, the controlled sensor mobility has been especially useful to maintain the connectivity among sensors assuring real-time data dissemination (Ekici *et al.*, 2006), to extend the WSN lifetime by replacing sensors with low energy (Basagni *et al.*, 2008; Jain *et al.*, 2006), to improve WSN spatial coverage avoiding holes (Wang *et al.*, 2009), and to improve monitoring by moving sensors closer to events (Butler and Rus, 2003).

Although a large amount of studies have been carried out about WSNs and forest fire risk monitoring, none of them has taken advantage of the controlled sensor mobility. In this regard, controlled mobility can play an important role when, due to the fire risk variability, sensors may end up covering the dynamic phenomenon wrongly. How well the sensors cover a phenomenon within a region of interest is known as WSN spatial coverage (Liu *et al.*, 2005). Enhancing WSN spatial coverage entails considering sensor behaviour such as sleeping and moving, that are constrained by both the phenomenon and the WSN. For instance, different fire risk intensities require the configuration of different WSN coverage densities. This can be achieved by moving sensors towards hotspots needing a higher coverage density. Additionally, the low energy of sensors can constrain the moving behaviour in order to save energy. However, if there is a concurrent emergency situation with high fire risk, the energy factor should not constrain the behaviour any longer. In this context, it becomes critical to monitor the fire risk properly rather than to save energy. Therefore, our research challenge focuses on the inference of mobile sensor behaviour, bearing in mind mobility constraints on the phenomenon as well as the sensing system itself. Particularly, our concern is about whether sensor behaviour should change to achieve suitable spatial coverage of a dynamic phenomenon such as forest fire risk.

This paper presents a model to make explicit mobility constraints of sensors. The mobility constraint model aims to probabilistically infer behaviour of mobile sensors in the scope of forest fire risk monitoring. The model follows a Bayesian network, centralised approach. It consists of three components: (1) a context typology using metadata to describe different contexts in which a WSN monitors a dynamic phenomenon; (2) a context graph encoding probabilistic dependencies among variables about mobility constraints within the different contexts; and (3) contextual rules encoding expert knowledge and application requirements needed for the inference of sensor behaviour. The Bayesian network approach has been chosen to provide a useful way of dealing with complex dependencies among variables. This is done by combining robust probabilistic methods with the clarity of graphs (Jordan, 1998). The probabilistic dependencies among variables can be obtained from data as well as from expert domains. This is crucial whenever data are not available due to high cost or just impossible to observe (Wiegerinck *et al.*, 2010). Moreover, Bayesian networks can update and propagate probabilities to obtain the current state of the mobility constraints, which is essential in a highly dynamic environment. We have simulated the deployment of a mobile WSN. The monitoring has used the Fuel Fine Moisture Code (FFMC) of the Canadian Fire Weather Index, as an indicator of the relative ease of ignition (Lawson and Armitage, 2008). Two scenarios have illustrated the inference of mobile sensor behaviour to enhance the spatial coverage. One with low fire risk to exemplify the inference of sleeping sensor behaviour; and the other with a higher fire risk level to mainly infer moving sensor behaviour.

This paper starts describing related studies about forest fire applications, WSNs and Bayesian networks. Then the mobility constraint model is presented through an incremental explanation of its three components (context typology, context graph, and contextual rules), and how they are employed in fire risk monitoring. Section 3.4 provides the inference of sensor behaviour within the mobility constraint model. Section 3.5 reports the results based on low and high fire risk scenarios. Finally, a discussion and conclusions are presented, as well as our anticipated future research.

3.2. RELATED STUDIES

Several studies have been carried out using WSNs in forest fire applications. They have efficiently detected forest fires based on weather data captured using immobile WSNs (Doolin and Sitar, 2005); they have monitored fire behaviour combining weather data and visual images provided by cameras (Hartung *et al.*, 2006); and they have also monitored the kinematics of spreading fire to support fire fighting strategies (Antoine-Santoni *et al.*, 2009). Nevertheless, these studies have employed immobile WSNs for the detection of already started fires. By contrast, our focus is on mobile WSNs for monitoring forest fire risk.

Hefeeda and Bagheri (2008) have developed an early detection procedure for forest fires. The authors have monitored fire risk using WSNs and the Canadian Fire Weather Index (Lawson and Armitage, 2008). The forest fire risk issue has been modelled as a coverage problem employing an overpopulated immobile WSN. The sensors could go to sleep and wake up creating a balance in the energy consumption in order to stretch out WSN lifetime. These sleeping and waking up mechanisms have also provided various coverage densities to obtain higher accuracies in specific areas. The relevance of this study is the consideration of coverage density variations in forest fire risk monitoring.

Regarding mobile sensors, two studies are worth being mentioned. Sahin (2007) has detected fires with mobile sensors attached to animals using two methods: one based on thermal detection, and another one based on animal behaviour classification, e.g. panic behaviour could be a fire indicator. In this study, the mobility was uncontrolled, and for that reason it was not possible to change the behaviour of the mobile sensor. Moreover, Erman *et al.* (2009) have used mobile WSNs cooperating with unmanned aerial vehicles (UAVs) for mission critical management involving fire detection. The main focus was on the data delivery with energy cost analysis and reliability of the routing protocol rather than on the expected behaviour of the mobile sensors in relation to the fire detection itself.

Furthermore, Dlamini (2010) has used Bayesian networks to determine biotic, abiotic and human factors that most influence the occurrence of fire in Swaziland. This study has shown how domain knowledge and limited empirical and GIS data can be combined within a Bayesian network. However, the study has been based on historical fire data without any integration with real-time data.

Despite the large amount of studies carried out about forest fires and WSNs, none so far had taken advantage of controlled sensor mobility. Therefore, this paper contributes to fill this gap by proposing a mobility constraint model to probabilistically infer the behaviour of mobile sensors.

3.3. MOBILITY CONSTRAINT MODEL

We propose a model for mobility constraints on the phenomenon and the WSN itself to be made explicit. It makes use of a Bayesian network approach and allows the probabilistic inference of the most suitable sensor behaviour. The following sections present the model components, starting with the description of the context typology, continuing with a theoretical description of the context graph and the selected variables about mobility constraints in fire risk monitoring and finishing with the use of contextual rules.

3.3.1. The context typology

The objective of the context typology is to describe the situation in which a WSN is monitoring a dynamic phenomenon from different perspectives. It consists of four types of contexts: sensor, network, sensing, and organisation (Ballari *et al.*, 2009). The sensor context describes each individual sensor in terms of location, energy and type of mobility. The network context, which in turn contains the sensor context, describes the WSN as a whole. It describes the interrelation and cooperation among sensors such as spatial coverage extension, spatial coverage density, and neighbours. The sensing context describes the monitored phenomenon and its current spatial distribution and intensity. Moreover, the sensing context can be described for each individual sensor as well as for the whole WSN. Finally, the organisation context describes application requirements and objectives of the monitoring. The latter is the most general context; it contains all the other types. Figure 3.1 shows a diagram of the contexts.

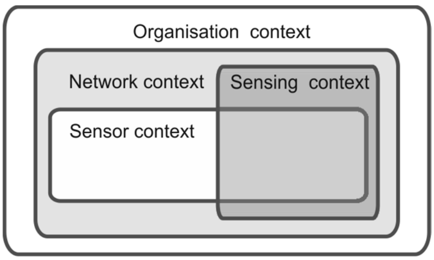

Figure 3.1. Diagram of the four types of contexts.

The four types of contexts are not isolated from each other. Dependencies exist among them in the sense that what happens within one context could affect what happens within the others (Giunchiglia, 1993). For instance, the sensor location (sensor context) can change due to mobility affecting the spatial coverage extension and density (network context). Furthermore, these dependencies can also exist within the same context. For instance, an increase of the value of the Fine Fuel Moisture Code – FFMC (sensing context) can also produce the increase of the fire risk level (sensing context).

The description of the contexts is made using metadata, and the relationships between metadata represent dependencies within a context and among different contexts. Metadata have been widely defined as descriptive data about data. This definition has also been extended to describe processes, functionalities, systems, and even situations. Although in practice the distinction between data and metadata is not always clear, we make the following consideration. Data are exclusively sensing data captured by the WSN (e.g. temperature, GPS location), whereas metadata are descriptive data about the WSN (e.g. energy level, type of mobility), and further computed data based on the sensing data (e.g. FFMC, spatial coverage). The reason for this distinction is to make use of metadata as descriptors of what is happening in the different contexts, regardless of whether some metadata could also be considered as data in other applications outside our model.

3.3.2. The context graph

A context graph is a Bayesian network, which in turn is a directed acyclic graph that encodes probabilistic dependencies among random variables of interest (Charniak, 1991; Jensen and Nielsen, 2007; Pearl and Russell, 2001). The structure of this context graph consists of nodes representing the variables, each variable having a finite set of mutually exclusive states and edges representing dependencies or relationships among these variables. According to the directionality of the edges, a set of parent and child variables can be defined. Moreover, the strength of the dependencies between variables is encoded by conditional probabilities. To each variable B with parents pa(B), a conditional probability table P(B|pa(B)) is attached. This table shows the conditional probability of the variable B having a certain state, given the occurrence of some state of its parents. Figure 3.2 shows an example of a Bayesian network.

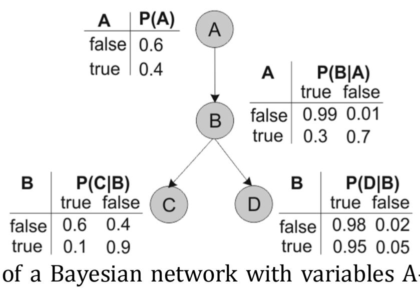

Figure 3.2. An example of a Bayesian network with variables A–D; true and false states and conditional probability tables for the variables are shown. For instance, P(B|A) can be read as the conditional probability of B given the probability of its parent A.

In our approach, metadata describing the four types of contexts are used as variables on mobility constraints. The edges between the variables represent dependencies among the contexts as well as within the same context. We distinguish different types of variables: (1) observed variables fed with metadata captured by the WSN as well as predefined metadata about the WSN configuration and requirements. Examples are the sensor id, the energy level and the extension of the region of interest the WSN should monitor; (2) computed variables fed with computed metadata based on sensing data and other metadata. For instance, temperature and humidity can be used to compute a more complex phenomenon such as forest fire risk; and (3) inferred variables based on other variables, since there are neither observed nor computed metadata about them.

Whether related variables are observed or computed, the conditional probability tables can be learned from metadata values. The goal of the learning is to find the values for each conditional probability table which maximises the likelihood of the metadata values (Binder *et al.*, 1997; Heckerman, 2008). In our model we use the Expectation–Maximisation-EM learning algorithm (Dempster *et al.*, 1977). It handles incomplete datasets which are common in WSNs due to loss of connectivity among sensors. These conditional probability tables are updated every time new metadata values feed the context graph.

By contrast, in the case of inferred variables, there are no metadata values that can be used to learn conditional probabilities. Thus contextual rules enable us to define the expected strength of the dependencies between variables. A further explanation about contextual rules is provided in Section 3.3.3.

Furthermore, the context graph allows probabilistic inference by probability propagation. It concerns the problem of computing the conditional probability distribution of a subset of variables given another subset of variables. It propagates the probabilities throughout the graph to deduce the inferred variables based on the observed and computed ones. In other words, the probability propagation is the action of updating the probabilities in each variable in the graph when metadata are given (Jordan, 1998). Conceptually, the posterior probability $P(B|A)$ is calculated using the Bayes rule $P(B|A) = P(A|B)P(B)/P(A)$. However, computationally, this calculation is hard and inefficient. Methods, such as junction trees, exploit the structure of the context graph in order to derive an efficient exact inference algorithm (Needham *et al.*, 2007). A detailed explanation can be found in (Huang and Darwiche, 1996).

Variables about mobility constraints in forest fire risk monitoring

In this section, we present the variables for the mobility constraints in forest fire risk monitoring. The mobility constraints belong to the different types of contexts. Some variables are application-independent, others are not. The next paragraphs, with the help of Figure 3.3 and Table 3.1, explain the variables in detail. In Figure 3.3 the variables are grouped in seven different sections (a–g) to provide a sound explanation.

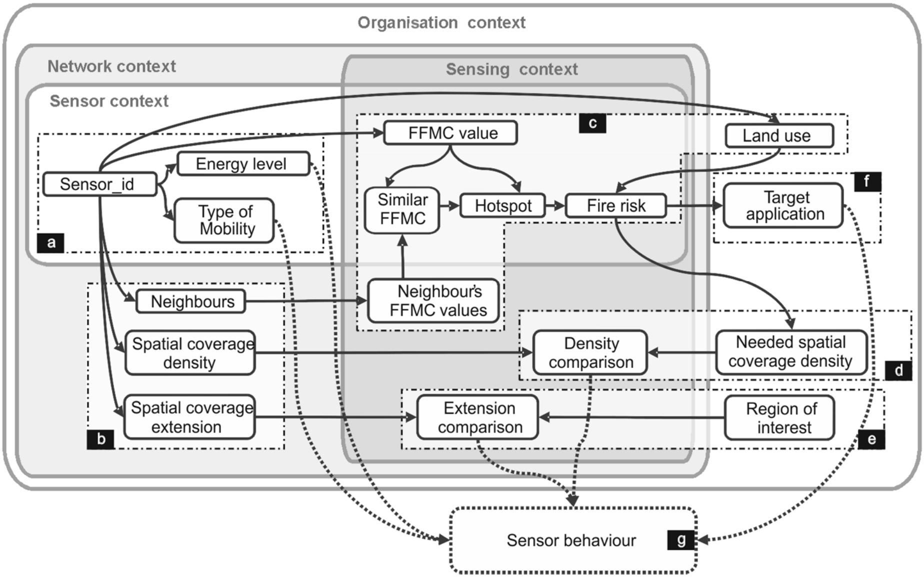

Figure 3.3. Metadata as variables for the mobility constraints within the four types of contexts. As background the diagram of the contexts is provided. Sections a-g represent grouped variables according to the explanation provided in the text. The solid edges represent dependencies between the variables, while the dotted edges relate the sensor behaviour to the variables that actually constrain such a variable. For further details about the variables see Table 3.1.

Within the sensor context (Figure 3.3, section-a), there are three application-independent variables. The *sensor id* with the deployed sensors in the WSN; the *energy level*, containing the remaining energy of each sensor; and the *type of mobility*, indicating whether sensor mobility is controlled or uncontrolled.

Within the network context (Figure 3.3, section-b), there are three application-independent variables. They are children of the sensor id and are computed using the GPS geographical location of the sensors. The *neighbours* are sensors located in a geographical range of, for instance, 20 m. The *spatial coverage density* is the number of neighbours a sensor has within the 20 m of range. Finally, the *spatial coverage extension* is the spatial aggregation of the individual spatial coverages of the sensors at an instant of time. It depends on the number of deployed sensors, their location, and their individual spatial coverages. The individual spatial coverage is a buffer centred on the sensor location usually having a radius of 10 m (Hossain *et al.*, 2008; Huang and Tseng, 2005).

Within the sensing context (Figure 3.3, section-c), there are application-dependent variables about forest fire risk monitoring. The *FFMC value* is the Fuel Fine Moisture Code (FFMC) of the Canadian Fire Weather Index. It expresses the moisture content of litter and other small forest fuels (surface litter, leaves, needles and small twigs). It is an indicator of the relative ease of ignition and flammability of fine fuels (Lawson and Armitage, 2008). The FFMC value near each sensor is computed with empirical equations (Van Wagner and Pickett, 1985). They use the temperature and humidity retrieved by the sensors, and the wind speed and rainfall retrieved by the nearest weather station. The FFMC value can also be classified into low or high values. Based on Hefeeda and Bagheri (2008), in our model the threshold between low and high values is 85. Moreover, the *neighbours' FFMC values* are also computed. The *similar FFMC* shows whether the FFMC values of a sensor and its neighbours are similar so as to estimate a confidence level on them. The presence or absence of a *hotspot* is inferred near the location of a sensor. Finally, the level of the *fire risk* is inferred considering the hotspot and the type of land use where the sensor is located.

Section-d of Figure 3.3 shows the *needed spatial coverage density* according to fire risk. The *density comparison* shows whether the current spatial coverage density is or is not enough to provide a needed density. A similar approach is used for the *spatial coverage extension* (Figure 3.3, section-e). The *extension comparison* highlights whether the current spatial coverage extension is or is not enough to cover a predefined region of interest.

The organisation context (Figure 3.3, section-f) contains the *target application* as an application-dependent variable. It shows whether the fire risk evolves from a normal into an emergency situation due to high fire risk. Other variables in this context are the *land use*, the *needed spatial coverage density*, and the *region of interest*.

Finally, in section-g of Figure 3.3, the sensor behaviour is inferred to achieve a suitable spatial coverage of the forest fire risk. It is related to whether sensors should move, sleep or the deployment of more sensors is required. Different mobility constraints have been considered within the different types of contexts. In the sensor context, the sensor energy and the type of mobility constrain the sensor behaviour. The mobility of sensors with a low energy should be avoided. Moreover, the uncontrolled mobility prevents changing sensor location. In the sensing and network contexts, different fire risk levels entail the configuration of different WSN coverage densities. Then the sensors should move towards hotspots with high fire risk to achieve the needed density.

Also in the sensing and network contexts, the extension of the spatial coverage often changes due to mobility and sleeping sensors, and the region of interest might be insufficiently covered. Therefore, the sensors should move or wake up to appropriately cover the region of interest as much as possible. Finally, in the organisation context, if the target application is an emergency with high fire risk, the behaviour should be different than in a normal situation, e.g. the energy will not constrain the sensor behaviour any longer.

Table 3.1 Outline of the metadata as variables in the context graph.

Type of contexts	Variables (metadata)	Types of variables	Application dependent	Conditional probability tables
Sensor	Sensor id	Observed	No	Learned
	Energy level	Observed	No	Learned
	Type of mobility	Observed	No	Learned
Network	Neighbours	Computed	No	Learned
	Spatial coverage density	Computed	No	Learned
	Spatial coverage extension	Computed	No	Learned
Sensing	FFMC value	Computed	Yes	Learned
	Similar FFMC	Inferred	Yes	Contextual rule
	Hotspot	Inferred	Yes	Contextual rule
	Fire risk	Inferred	Yes	Contextual rule
	Neighbours' FFMC values	Computed	Yes	Learned
	Density comparison	Inferred	No	Contextual rule
	Extension comparison	Computed	No	Learned
Organisation	Land use	Computed	Yes	Learned
	Target application	Inferred	Yes	Contextual rule
	Needed spatial coverage density	Inferred	Yes	Contextual rule
	Region of interest	Observed	No	Learned
	Sensor behaviour	Inferred	Yes	Contextual rule

3.3.3. The contextual rules

In the case of observed and computed variables, metadata values are used to learn the conditional probabilities. In the case of inferred variables, however, this is not feasible because metadata can be very costly or impossible to obtain. Then the use of contextual rules allows encoding the expected strength of the dependencies among the variables. Contextual rules are obtained from prior studies, expert domain and application requirements (Wiegerinck *et al.*, 2010). Assessing these rules can be hard, so that methods for knowledge elicitation from domain experts are useful (Pollino *et al.*, 2007; Woodberry *et al.*, 2005). By contrast to the learning case, conditional probabilities from the contextual rules are static over time unless the expert knowledge and requirements have changed. In such a particular case, the contextual rules may require to be updated.

The contextual rules play the role of dependencies and constraints. In the first case, they encode the dependencies of inferred variables. They can be in the same context (hotspot and fire risk) or between different contexts (similar FFMC values, needed spatial coverage density, density comparison and target application). In the second case, the contextual rules play the role of constraints. They encode how the mobility constraints are expected to constrain the sensor behaviour. They bring the mobility constraints together following a centralised approach, although they belong to different contexts. Figure 3.4 shows an example of a contextual rule expressing the dependency between the fire risk and the target application.

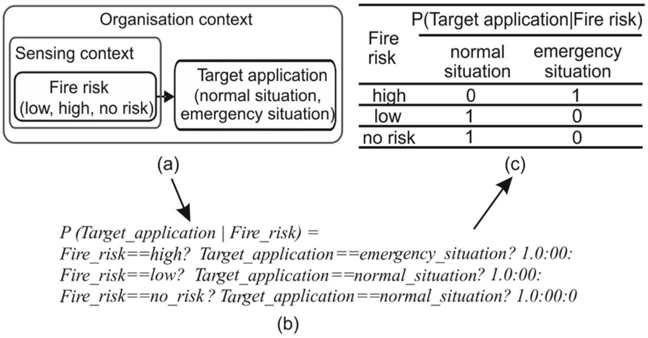

Figure 3.4. An example of a contextual rule: (a) context graph with two inferred variables in different contexts. They are the fire risk with three states (low, high and no risk) and the target application with two states (normal situation and emergency situation); (b) the contextual rule for expressing how the fire risk conditions the target application. The syntax of the contextual rule is concordant with the equations in Netica software; and (c) the contextual rule translated into a conditional probability table.

3.4. INFERENCE OF SENSOR BEHAVIOUR

By definition, inference is the process of deriving conclusions from premises. Whenever these conclusions are drawn following the laws of probability, the inference is probabilistic. In our case it consists of outlining the chance of sensors changing their behaviour given mobility constraints. This inference is as follows: first, metadata values feed the context graph to learn the conditional probabilities of all the observed and computed variables. Then these probabilities are propagated throughout the context graph in agreement to the contextual rules. This also carries out the deduction of the inferred variables consisting of: (1) the presence or absence of a hotspot near the location of a sensor; (2) the fire risk level in a hotspot; (3) the need to increase the coverage density by adding neighbours, or on the contrary, the need to decrease it by reducing neighbours; (4) the target application; and finally, (5) the most suitable sensor behaviour about whether sensors should move, sleep or the deployment of more sensors is required. The contextual rules for the inferred variables in Figure 3.3 are explained in detail in Appendix A.

3.5. SCENARIOS

Two scenarios are presented to illustrate the inference of sensor behaviour. One of them simulated low fire risk level to exemplify the inference of the sleeping behaviour. The other one simulated a higher fire risk level to mainly address the inference of moving behaviour. Both scenarios were based on the same spatial distribution of sensors, whereas different computed FFMC values illustrated the variation in spatial distribution and intensity of the forest fire risk (Figure 3.5).

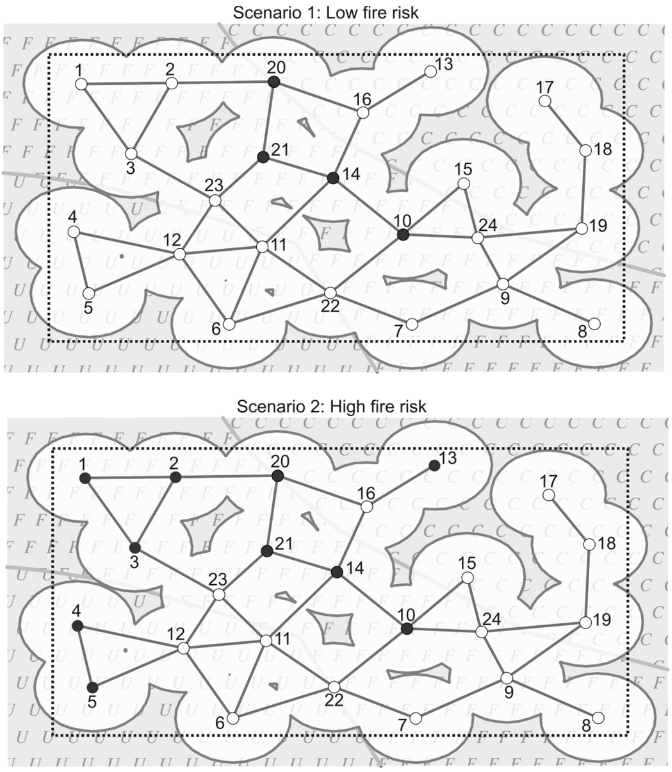

Figure 3.5. Deployment of a WSN in scenarios 1 and 2. The region of interest is represented by the dotted line square. Points represent the location of sensors, and lines between them their neighbourhood relations. The white points are low FFMC values, whereas the black points are high FFMC values. Buffers around the sensors are their individual coverages, which, when aggregated, define the spatial coverage extension of the WSN. The land uses, with urban areas filled with 'U' lettering, forest filled with 'F' lettering and camping filled with 'C' lettering, are provided as background.

3.5.1. WSN deployment and metadata computation

We simulated the deployment of a WSN with 24 sensors attached to robots, in an area of interest of 6467 m^2 (Figure 3.5). The sensors were equipped with the environmental MTS420 sensor board of MEMSIC, ex-Crossbow (MEMSIC, 2010). They captured and disseminated the temperature, humidity and GPS sensor location every 10 min (i.e. sampling rate). All the sensors had a controlled type of mobility. They could move, although they were kept fixed until changes in behaviour were induced.

Sensing data and metadata, which are used to learn conditional probabilities, were gathered from the WSN according to the sampling rate. They were processed in a PostgreSQL–PostGIS database (PostGIS, 2007). Table 3.2 describes the requirements for input data, and the respective outputs for the computed variables. Table 3.3 provides examples of the observed and computed metadata values.

Table 3.2 Requirements for input data and outputs for the computed variables (metadata).

Types of contexts	Variables (metadata)	Inputs	Outputs
Network	Neighbours	GPS sensor location	Sensors located within the range of 20m
	Spatial coverage density	Neighbours	Number of sensor neighbours
	Spatial coverage extension	GPS sensor location; individual coverage (10m)	Spatial polygon aggregating all the individual coverages at an instant of time
Sensing	FFMC value	Temperature and humidity capture by the sensors, and rainfall and wind speed capture by a weather station	FFMC value per sensor classified in low and high values.
	Neighbours' FFMC values	Neighbours, temperature and humidity captured by the sensors, and rainfall and wind speed captured by a weather station	FFMC value per sensor neighbour classified as low and high values
	Extension comparison	Spatial coverage extension; region of interest	Spatial comparison between both polygons. It is classified as enough (more than 80%) and insufficient (less than 80%)
Organisa-tion	Land use	Land use map; GPS sensor location	Land use nearby the location of each sensor (forest, urban, camping)

The context graph of Figure 3.3 was implemented as a Bayesian network in Netica (2009), with the contextual rules encoded as equations in each inferred variable. Learning was performed with the Expectation–Maximisation-EM algorithm implemented in Netica (Dempster *et al.*, 1977). This was carried out in an offline fashion using the available computed metadata values at the time of learning. This provided the current state of mobility constraints, i.e. previous constraints were not taken into account. For probability propagation and inference of sensor behaviour, the junction tree algorithm, also implemented in Netica, was used (Huang and Darwiche, 1996).

Table 3.3 Examples of observed and computed metadata values.

Sensor id	FFMC value	Energy level	Type of mobility	Neigh -bours	Spatial coverage density	Extension comparison	Land use
1	low value	high	controlled	(2,3)	2	enough_85	forest
2	low value	high	controlled	(1,3,20)	3	enough_85	forest
3	low value	high	controlled	(1,2,23)	3	enough_85	forest
4	low value	high	controlled	(12,5)	2	enough_85	urban
5	low value	high	controlled	(4,12)	2	enough_85	urban

3.5.2. Scenario 1: low fire risk

In this scenario only four sensors (16.7%) were located near high FFMC values (Figure 3.6a). There was a low fire risk with 16.5% probability, and no fire risk with 83.2% probability (Figure 3.6b). As a result, two different types of sensor behaviour were inferred (Figure 3.6c). First, with a 13.1% probability, sensors should not have changed their behaviour since they provided an appropriate coverage density (that was the case for sensors 8, 13, 15, and 17); and second, with an 86.9% probability, sensors should have been sent to sleep to reduce the coverage density (all the other sensors).

The only mobility constraint which actually had an influence on the behaviour was the coverage density, with the need of reducing the number of neighbours (density comparison variable). In terms of coverage extension, the sensors covered 85% of the region of interest, so that this was enough without constraining their behaviour (extension comparison variable). In addition, the energy level (i.e. mainly high), the type of mobility (i.e. controlled), and the target application (i.e. normal situation) did not constrain the behaviour in this scenario.

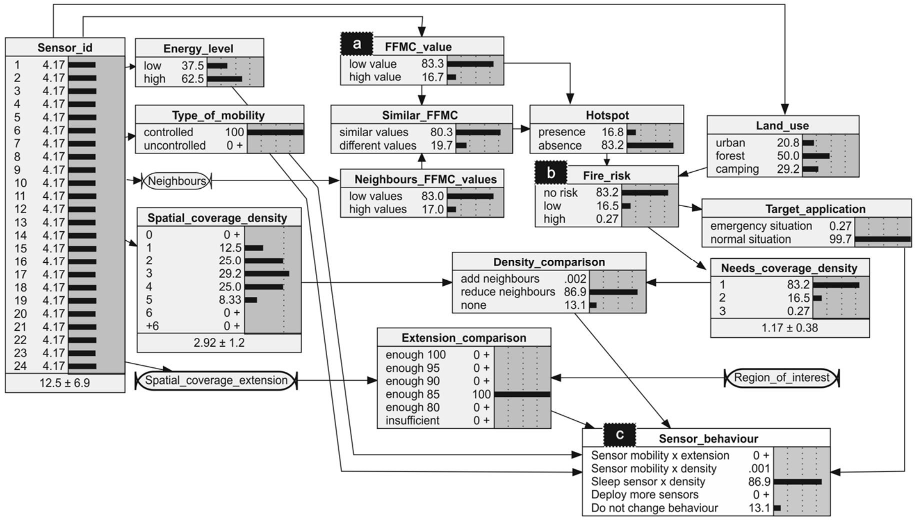

Figure 3.6. Context graph of scenario 1: (a) probability distribution of the Fine Fuel Moisture Code (FFMC value); (b) probability distribution of the fire risk; and (c) probability distribution of the inferred sensor behaviour (send to sleep sensors and do-not-change behaviour).

Although the main aim is to infer sensor behaviour, the same context graph can also be used to determine the most suitable sensors to be sent to sleep. Different variables can propagate their probabilities to update the sensor id variable, showing higher probabilities for the most suitable sensors to put to sleep. We considered they were: (1) sensors (and their neighbours) whose inferred behaviour was not do-not-change behaviour; (2) sensors with low energy to be sent to sleep in order to save energy; (3) sensors located near a no fire risk zone; and (4) sensors with a high spatial coverage density due to the fact that the impact of putting a sensor to sleep with 4 neighbours will be higher than a sensor with only 2 neighbours. Figure 3.7 shows how the sensor id was updated after the probability propagation mentioned above. As a result, the most suitable sensors to send to sleep were sensors 22, 23, and 24. Sensors should only be sent to sleep while the coverage extension is enough (more than 80% of the region of interest). Thus they were put to sleep one by one until the threshold of 80% was reached (Figure 3.7e). As a result of putting sensors 22, 23 and 24 to sleep, the probability of the sleeping behaviour was reduced from 86.9% to 71%, while the probability of maintaining the same behaviour was increased from 13.1% to 29%. Although the WSN was still providing more density than needed, further sensors could not be sent to sleep to avoid a coverage extension below the 80% threshold. Therefore, the inferred behaviour was do-not-change behaviour with 100% probability.

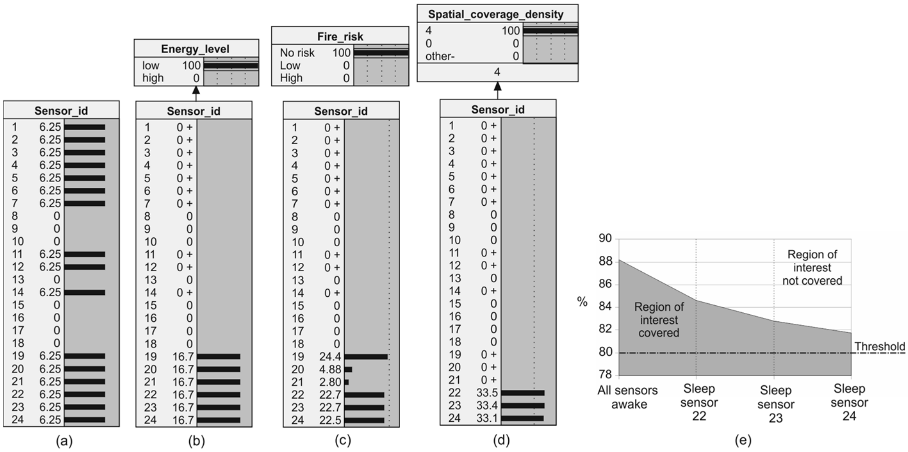

Figure 3.7. Probability propagation and updating to find the most suitable sensors to send to sleep in scenario 1: (a) sensors (and their neighbours) whose inferred behaviour was not do-not-change behaviour; (b) sensors with low energy; (c) sensors located near a no fire risk zone; (d) sensors with a coverage density of 4 neighbours; and (e) impact on the coverage extension when sensors 22, 23 and 24 are put to sleep.

3.5.3. Scenario 2: high fire risk

In the second scenario, the spatial distribution of the sensors was the same as in scenario 1, however the computed FFMC values were not (Figure 3.5, scenario 2). Figure 3.8a shows a higher number of sensors located near high FFMC values (41.7%). The fire risk was high with 7.86% probability, low with 32.2% probability, and there was no fire risk with 59.9% probability (Figure 3.8b). As a result, three different sensor behaviours were inferred (Figure 3.8c). First, with 9.99% probability sensors should have moved to increase the coverage density of sensors 4, 5 and 13; second, with 14.3% probability sensors should not have changed their behaviour since they provided an adequate coverage density (sensors 8, 13, 15, and 17); and third, with 75.7% probability sensors should have been sent to sleep to reduce the coverage density (all the other sensors). Although in this scenario the probability of high fire risk was still low (7.86%), the aim was to show how a higher level of fire risk addressed the inference of different sensor behaviour.

It should be emphasised that for sensor 13 two types of behaviour with different probabilities were inferred. Do-not-change behaviour with 30% probability and sensor mobility for density with 70% probability. The reason for this is that sensor 13 was located near a high FFMC value, and its neighbour (sensor 16) near a low FFMC value. Then this was propagated to the no fire risk (30% probability) and the low fire risk (70% probability), giving as a result two inferred behaviours for the same sensor.

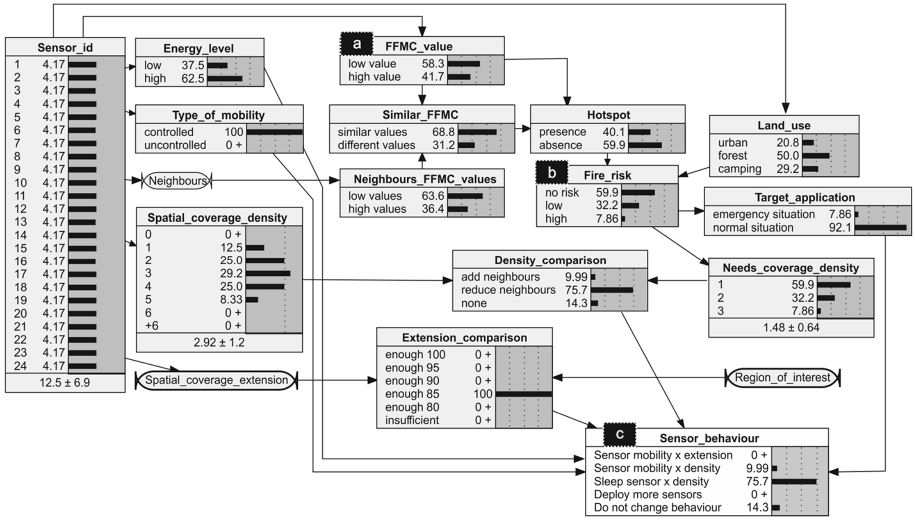

Figure 3.8. Context graph of scenario 2: (a) probability distribution of the Fine Fuel Moisture Code (FFMC values); (b) probability distribution of the fire risk; and (c) probability distribution of the inferred sensor behaviour (sensor mobility for density, send to sleep sensors and do-not-change behaviour).

The mobility constraints were the coverage density, with the need to increase density in some sensors and to reduce it in others; the type of mobility, since the moving behaviour was possible given the controlled mobility; and the high energy level which also allowed the moving behaviour. The target application did not constrain the sensor behaviour in view of the high energy level. In terms of coverage extension, it was sufficient because the sensors covered 85% of the region of interest.

The context graph allows us knowing the most likely sensors to move. They were: (1) sensors (and their neighbours) whose inferred behaviour was neither sensor mobility for density nor do-not-change behaviour; (2) sensors with high energy level; (3) sensors located near a no fire risk zone; and (4) close sensors to those requiring a density increment (sensors 4, 5 and 13). As a result, sensor 6 was moved near sensors 4 and 5, and sensor 11 was moved near sensor 13.

After moving the sensors, the metadata values were re-computed and the context graph inferred the behaviour of sleeping sensors (76.8% probability) and do-not-change behaviour (23.2% probability). The most likely sensors to go to sleep were found as in scenario 1. As a result, sensors 23 and 24 went to sleep. Figure 3.9 shows the resulting spatial distribution of sensors and the updated context graph. The WSN was still providing more coverage density than needed (63.5% of reduce neighbours in the density comparison variable). However, sensors could not be sent to sleep to avoid a coverage extension below the 80%

threshold. Thus, the inferred behaviour was do-not-change behaviour with 100% probability.

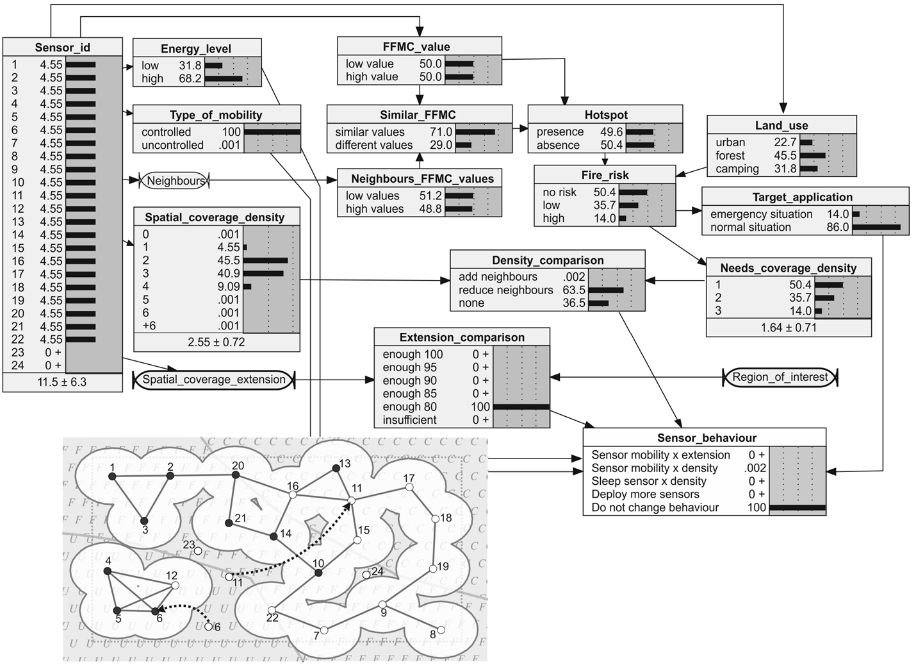

Figure 3.9. Context graph and spatial distribution of sensors in scenario 2 after moving sensors 6 and 11, and sleeping sensors 23 and 24.

3.6. DISCUSSION AND CONCLUSIONS

This paper focuses on the inference of mobile sensor behaviour in the scope of fire risk monitoring following a Bayesian network approach. The purpose of the behaviour is to achieve a WSN spatial coverage in agreement with the dynamics of the fire risk. This enables a more detailed monitoring wherever fire is more prone to occur while efficiently using the available WSN resources. Our main contribution is a mobility constraint model in which a context graph, modelled as a Bayesian network, makes different mobility constraints explicit within four context types: sensor, network, sensing, and organisation. Metadata values about the phenomenon and the WSN are used to feed the context graph, and the probabilities are propagated following the graph structure and the defined contextual rules. It is shown, based on low and high fire risk scenarios, that the implemented model can successfully infer the most suitable sensor behaviour by handling, through conditional probabilities, the different mobility constraints. As a result, the behaviour was inferred about whether it was more suitable to send sensors to sleep, to move them to enhance coverage density and extension, to deploy more sensors, or on the contrary, to maintain current behaviour.

The main advantage of having the mobility constraint model designed as a Bayesian network is the probability propagation. Any learned change in the spatial distribution and intensity of the fire risk as well as in the WSN itself (e.g. energy, location, etc.), is propagated throughout the context graph with the inference of the most suitable behaviour. Although the main outcome is the inference of behaviour, the same model can also be used to obtain useful information about the most suitable sensors on which to implement the sleeping and moving behaviour. In addition, the mobility constraint model also allows representation of the four types of contexts at the same time and within the same context graph. This is important for maintaining links between the behaviour of sensors and the impact they can have on the different contexts, e.g. when the inferred behaviour is to make a sensor sleep, but this is not possible because of an insufficient coverage extension at the network context.

A weakness of the model is that the variables about mobility constraints need to be explicitly defined and related in the context graph. The contextual rules are useful to encode the expert knowledge about the variables when they cannot be directly learned from metadata values. Evaluation of these rules can be made by using methods developed in the field of knowledge engineering (Pollino *et al.*, 2007; Woodberry *et al.*, 2005). The pitfall, however, is that contextual rules may involve a high number of variables with several states. That increases the complexity, making implementation more difficult. Table A7 in Appendix A is an example of this. Moreover, the contextual rules can drive the inference of more than one type of behaviour, as it was shown for sensor 13 in scenario 2. In order to discern which behaviour should be really carried out, the criterion of the highest probability could not always be the most advisable. By contrast, it would be necessary to consider the behaviour with the lowest probability, but with a crucial implication for the application. Therefore, further analysis is still needed in order to shed light on how pronouncements about different types of behaviour can be encoded within the mobility constraint model.

Learning conditional probabilities was performed in such a way that only the current mobility constraints were considered, i.e. previous constraints were not taken into account. However, for some variables, especially those belonging to the sensing context, it could be useful to study the impact to learn them incrementally (i.e. using online instead of offline learning).

The mobility constraint model followed a centralised approach by gathering together mobility constraints from different contexts. The counterpart is twofold; first, more sensor energy is consumed to centralise metadata; and second, sensors may become isolated without being able to infer behaviour by themselves (Coles *et al.*, 2009; Duckham and Reitsma, 2009). Nevertheless, the centralised approach allows the inference of more complex behaviour involving cooperation of sensors. This is the case when moving a sensor to increase the coverage density of another sensor. Hence, it would be worthwhile making a compromise between decentralised and centralised approaches to infer the behaviour with as much local knowledge as possible but still being able to depict the global picture.

Spatial knowledge in our model is represented through different variables such as neighbours, coverage density and extension. However, at this moment, spatial knowledge is only involved as premises in the inference. Deductions about spatial relations are still missing. This is essential, for instance, to know whether sensors are located at the same hotspot and to handle scenarios with multiple and disparate hotspots. In view of the significance of the spatial knowledge in our model, it is necessary to explore further approaches to carry out deductions based on spatial analysis and support the situations mentioned above. In our implementation, and for the sake of simplicity, we have defined the initial spatial density of sensors in an ad hoc manner. This could be improved by extending our model with the approach of Hefeeda and Bagheri (2008), in which a required spatial density was computed with the aim of achieving a given accuracy level in forest fire risk estimation. Moreover, the mobility constraint model is not meant to infer the exact new location and trajectory of the sensors. In order to do that, other supplementary techniques, such as geostatistics, will be needed to precisely determine the future sensor location (Heuvelink *et al.*, 2010). We have not considered mobility constraints associated with the geographical space itself, such as buildings, rivers, lakes and trees.

Our model can also be useful in a fire detection application, although the sensors behave differently than in fire risk monitoring. For instance, they should also move to detect boundaries of a burning zone. Our model can also be used for monitoring other environmental phenomena such as air pollution, noise and soil moisture. In those cases, application-dependent variables (see Table 3.1) should be adapted in accordance with the phenomenon of interest. Contextual rules should also be reviewed in order to properly encode application requirements and expert knowledge from the domain of interest. Our study is restricted to outdoor environments since the spatial computation is based on GPS location data. For indoor environments and WSN without GPS, it should be necessary to consider other location techniques such as beacon sensors and proximity- based location (Yick *et al.*, 2008).

Regarding a real implementation, it would be necessary to consider communication issues such as connectivity and flow of information between the model and the WSN. The computation of the Fine Fuel Moisture Code relies on observations retrieved by the sensors and the nearest weather station. When the weather data of one station result in too coarse information, it might be necessary to deploy an additional weather station in the area of interest. In addition, some research is still needed to address how adjustments provided by sensor behaviour improve the efficiency of the monitoring. The study of Hefeeda and Bagheri (2008) could be a good starting point to address this issue in the sense that it analysed how spatial coverage density can be used to improve the efficiency of forest fire risk monitoring.

The knowledge of how mobile sensors should behave in the presence of mobility constraints is an important step towards mobile sensing. Although this paper is based on simulated scenarios, it provides a useful demonstration of how the mobility constraint model can successfully handle low level information such as metadata in order to infer sensor behaviour. Our future research will focus on expanding the mobility constraint model to be able to tell apart different types of behaviour. It will also explore further approaches to carry out inferences based on spatial analysis. Finally, it would be useful to evaluate the model in a more realistic scenario, taking also into account spatiotemporal dynamics of the fire risk. That would allow us understanding sensor behaviour from a spatiotemporal dimension.

Appendix A. Contextual rules for the inferred variables

A.1. Hotspot

It consists of the inference of the presence or absence of a hotspot near the location of a sensor. In order to achieve that, it is necessary to know if the computed FFMC values for this particular sensor and its neighbours are similar and, at the same time having values higher than the threshold of 85. Therefore, two contextual rules have been defined. The first one describes the dependency between the similar FFMC values and two premises: the FFMC value of each sensor and the neighbours' FFMC values. The second one relates the similar FFMC values and the hotspot. Tables A1 and A2 provide the contextual rules and the conditional probability tables for the inferred variables.

Table A1 Contextual rule (dependency) and conditional probability table for the inference of the similar FFMC values (Fine Fuel Moisture Code).

P (Similar_FFMC | FFMC_value, Neighbours_FFMC_values) =
FFMC_value==low_value && Neighbours_FFMC_values==low_values ?
Similar_FFMC==similar_values ? 1.0 : 0.0:
FFMC_value==low_value && Neighbours_FFMC_values==high_values ?
Similar_FFMC==different_values ? 1.0 : 0.0:
FFMC_value==high_value && Neighbours_FFMC_values==low_values?
Similar_FFMC == different_values ? 1.0 : 0.0:
FFMC_value==high_value && Neighbours_FFMC_values==high_values?
Similar_FFMC==similar_values ? 1.0 : 0.0:0

FFMC value	Neighbours' FFMC values	P(Similar FFMC | FFMC value, Neighbours' FFMC values)	
		similar values	different values
low value	low values	1	0
high value	low values	0	1
low value	high values	0	1
high value	high values	1	0

Table A2 Contextual rule (dependency) and conditional probability table for the inference of the hotspot.

P(Hotspot | FFMC_value, Similar_FFMC) =
FFMC_value==low_value && Similar_FFMC==similar_values?
Hotspot==absence? 1.0 : 0.0 :
FFMC_value==low_value && Similar_FFMC==different_values?
Hotspot==presence ? 0.3 : Hotspots == absence? 0.7 : 0.0:
FFMC_value==high_value && Similar_FFMC==similar_values?
Hotspot==presence? 1.0 : 0.0) :
FFMC_value==high_value && Similar_FFMC==different_values?
Hotspot==absence? 0.3 : Hotspots == presence ? 0.7 : 0.0:0

FFMC value	Similar FFMC values	P(Hotspot | FFMC value, Similar FFMC)	
		presence	absence
low value	similar values	0	1
high value	similar values	1	0
low value	different values	0.3	0.7
high value	different values	0.7	0.3

A.2. Fire risk

It consists of the inference of whether the forest fire risk at a hotspot is low or high, considering the type of land use near a sensor location. The premises are the inferred hotspot and the land use. The contextual rule considers that the presence of humans can increase the damages a fire could produce. Thus the risk should be higher at a hotspot located in an urban area than in a forest or camping area (Table A3).

Table A3 Contextual rule (dependency) and conditional probability table for the inference of the fire risk.

P (Fire_risk | Hotspot, Land_use) =
Hotspot==absence ? Fire_risk==no_risk? 1.0 : 0.0:
Hotspot==presence && Land_use == urban? Fire_risk==high? 1.0 : 0.0:
Hotspot==presence && Land_use == forest? Fire_risk==low? 1.0 : 0.0:
Hotspot==presence && Land_use == camping? Fire_risk==low? 1 :0.0:0

Hotspot	Land use	P(Fire risk | Hotspot, Land use)		
		no risk	low	high
presence	urban	0	0	1
absence	urban	1	0	0
presence	forest	0	1	0
absence	forest	1	0	0
presence	camping	0	1	0
absence	camping	1	0	0

A.3. Spatial coverage density comparison

It consists of the inference of whether an increase in the coverage density is needed because a hotspot may have been covered by an insufficient coverage density. Two contextual rules have been defined. One expresses the dependency between the fire risk and the needed spatial coverage density. It makes the following consideration: for high risk, the coverage density needs to be of at least 3 neighbours; for low risk, coverage density of at least 2 neighbours; and where there is no fire risk at all, density of at least 1 neighbour (Table A4). The second contextual rule relates the density comparison and two premises, the spatial coverage density and the needed spatial coverage density. It expresses the need of adding neighbours if a sensor near a high risk zone has less than 3 neighbours, near a low risk zone less than 2 neighbours, and near a no fire risk zone, less than 1 neighbour. Moreover, reducing neighbours might also be needed if a sensor near a high risk zone has more than 3 neighbours, near a low risk zone, more than 2 neighbours, or near a no fire risk zone, more than 1 neighbour (Table A5).

Table A4 Contextual rule (dependency) and conditional probability table for the inference of the needed spatial coverage density.

P (Needed_spatial_coverage_density | Fire_risk) =
Fire_risk==high? Needs_spatial_coverage_density==3? 1.0:00:

Fire_risk==low? Needs_spatial_coverage_density==2? 1.0:00: Fire_risk==no_risk? Needs_spatial_coverage_density==1? 1.0:00:0			
Fire risk	P (Needed spatial coverage density | Fire risk)		
	3 neighbours	2 neighbours	1 neighbour
no risk	0	0	1
low	0	1	0
high	1	0	0

Table A5 Contextual rule (dependency) and conditional probability table for the inference of the density comparison.

P(Density_comparison | Spatial_coverage_density,Needed_spatial_coverage_density)=
Spatial_coverage_density==0 ? density_comparison==add_neighbours ? 1.0 : 00:
Spatial_coverage_density==1 && Needed_spatial_coverage_densit==1?
Density_comparison==none? 1.0 : 00:
Spatial_coverage_density==1 &&Needed_spatial_coverage_density==2?
Density_comparison==add_neighbours? 1.0 : 00:
Spatial_coverage_density==1 && Needed_spatial_coverage_density==3 ?
Density_comparison==add_neighbours? 1.0 : 00:
Spatial_coverage_density==2 && Needed_spatial_coverage_densit==2?
Density_comparison== none? 1.0 : 00:
Spatial_coverage_density==2 && Needed_spatial_coverage_density==3?
Density_comparison==add_neighbours? 1.0 : 00:
Spatial_coverage_density==2 && Needed_spatial_coverage_density==1?
Density_comparison==reduce_neighbours? 1.0 : 00:
Spatial_coverage_density==3 && Needed_spatial_coverage_density==1?
Density_comparison==reduce_neighbours? 1.0 : 00:
Spatial_coverage_density==3 && Needed_spatial_coverage_density==2?
Density_comparison==reduce_neighbours? 1.0 : 00:
Spatial_coverage_density==3 && Needed_spatial_coverage_density==3?
Density_comparison==none? 1.0 : 00:
Spatial_coverage_density==+3 ? Density_comparison==reduce_neighbours? 1.0 : 00:0

(current) Spatial coverage density	Needed spatial coverage density	P(Density comparison | Spatial coverage density, Needed spatial coverage density)		
		add neighbours	reduce neighbours	none
0 neighbour	1 neighbour	1	0	0
0 neighbour	2 neighbours	1	0	0
0 neighbour	3 neighbours	1	0	0
1 neighbour	1 neighbour	0	0	1
1 neighbour	2 neighbours	1	0	0
1 neighbour	3 neighbours	1	0	0
2 neighbours	1 neighbour	0	1	0
2 neighbours	2 neighbours	0	0	1
2 neighbours	3 neighbours	1	0	0
3 neighbours	1 neighbour	0	1	0
3 neighbours	2 neighbours	0	1	0
3 neighbours	3 neighbours	0	0	1
+3 neighbours	1 neighbour	0	1	0
+3 neighbours	2 neighbours	0	1	0
+3 neighbours	3 neighbours	0	1	0

A.4. Target application

It consists of the inference of whether, considering the fire risk, a sensor carries out the monitoring in a normal or in an emergency situation (Table A6).

Table A6 Contextual rule (dependency) and conditional probability table for the inference of the target application.

P (Target_application | Fire_risk) =
Fire_risk==high? Target_application==emergency situation? 1.0:00:
Fire_risk==low? Target_application==normal_situation? 1.0:00:
Fire_risk==no_risk? Target_application==normal_ situation? 1.0:00:0

Fire risk	P (Target application | Fire risk)	
	normal situation	emergency situation
no risk	1	0
low	1	0
high	0	1

A.5. Sensor behaviour

It consists of the deduction of the behaviour given the mobility constraints (energy level, type of mobility, density comparison, extension comparison, and target application). The contextual rules and conditional probability are provided in Table A7. The following types of sensor behaviour are inferred:

Do-not-change sensor behaviour whether (1) the coverage density is in agreement with the fire risk, and the coverage extension sufficiently covers at least 80% of the region of interest; (2) or the coverage density needs to be reduced and sensors cannot be sent to sleep since the coverage extension does not cover more than 80% of the region of interest.

Deploy more sensors whether (1) the coverage extension is insufficient and/or the coverage density needs to add neighbours, and (2a) the type of mobility is uncontrolled, or (2b) although the type of mobility is controlled, the target application is a normal situation with a low energy level.

Move sensors to enhance coverage extension whether (1) the coverage extension is insufficient, the type of mobility is controlled, and (2a) the target application is a normal situation with a high energy level; or (2b) the target application is an emergency situation without considering the remaining energy.

Move sensors to enhance coverage density whether (1) the coverage density needs to add neighbours, the type of mobility is controlled, and (2a) the target application is a normal situation with a high energy level; or (2b) the target application is an emergency situation without considering the remaining energy.

Send to sleep sensors to enhance density whether (1) the coverage density needs to reduce neighbours, and (2) the coverage extension sufficiently covers more than 80% of the region of interest.

Table A7 Contextual rule (constraint) and conditional probability table for the inference of sensor behaviour.

P (Sensor_behaviour| Target_application, Energy_level, Type_of_mobility, Density_comparison, Extension_comparison) =
Density_comparison==none && Extension_comparison !=insufficient ? Sensor_behaviour==Do_not_change_behaviour?1.0:00:
Density_comparison==reduce_neighbours && Extension_comparison==enough_80? Sensor_behaviour==Do_not_change_behaviour?1.0:00:

Density_comparison==reduce_neighbours && Extension_comparison==enough_100? Sensor_behaviour==Sleep_sensor_x_density?1.0:00:
Density_comparison==reduce_neighbours && Extension_comparison==enough_95? Sensor_behaviour==Sleep_sensor_x_density?1.0:00:
Density_comparison==reduce_neighbours && Extension_comparison==enough_90? Sensor_behaviour==Sleep_sensor_x_density?1.0:00:
Density_comparison==reduce_neighbours && Extension_comparison==enough_85? Sensor_behaviour==Sleep_sensor_x_density?1.0:00:

Density_comparison==add_neighbours && Extension_comparison==insufficient && Type_of_mobility==uncontrolled? Sensor_behaviour==Deploy_more_sensors? 1.0:00:
Density_comparison !=add_neighbours && Extension_comparison==insufficient &&Type_of_mobility==uncontrolled? Sensor_behaviour==Deploy_more_sensors? 1.0:00:
Density_comparison==add_neighbours && Extension_comparison !=insufficient && Type_of_mobility==uncontrolled ? Sensor_behaviour==Deploy_more_sensors? 1.0:00:
Density_comparison==add_neighbours && Extension_comparison==enough_80 && Type_of_mobility==uncontrolled? Sensor_behaviour==Deploy_more_sensors? 1.0:00:
Density_comparison !=add_neighbours && Extension_comparison==enough_80 &&Type_of_mobility==uncontrolled? Sensor_behaviour==Deploy_more_sensors? 1.0:00:
Density_comparison==add_neighbours && Extension_comparison !=enough_80 && Type_of_mobility==uncontrolled ? Sensor_behaviour==Deploy_more_sensors? 1.0:00:

Density_comparison==add_neighbours && Extension_comparison !=insufficient && Type_of_mobility==controlled && Energy_level==high ? Sensor_behaviour==Sensor_mobility_x_density? 1.0:00:
Density_comparison==add_neighbours && Extension_comparison !=insufficient &&Type_of_mobility==controlled && Energy_level==low && Target_application==emergency_situation ? Sensor_behaviour==Sensor_mobility_x_density? 1.0:00:

Density_comparison==add_neighbours && Extension_comparison !=insufficient && Type_of_mobility==controlled && Energy_level==low && Target_application==normal_situation? Sensor_behaviour==Deploy_more_sensors? 1.0:00:

Density_comparison !=add_neighbours && Extension_comparison==insufficient &&Type_of_mobility==controlled && Energy_level==high ? Sensor_behaviour==Sensor_mobility_x_extension? 1.0:00:
Density_comparison !=add_neighbours && Extension_comparison==insufficient &&Type_of_mobility==controlled && Energy_level==low && Target_application==emergency_situation? Sensor_behaviour==Sensor_mobility_x_extension? 1.0:00:

Density_comparison !=add_neighbours && Extension_comparison==insufficient &&Type_of_mobility==controlled && Energy_level==low && Target_application==normal_situation? Sensor_behaviour==Deploy_more_sensors? 1.0:00:
Density_comparison==add_neighbours && Extension_comparison==insufficient && Type_of_mobility==controlled && Energy_level==low && Target_application==normal_situation? Sensor_behaviour==Deploy_more_sensors? 1.0:00:

Density_comparison==add_neighbours && Extension_comparison==insufficient && Type_of_mobility==controlled && Energy_level==high ? Sensor_behaviour==Sensor_mobility_x_extension? 0.5: Sensor_behaviour==Sensor_mobility_x_density? 0.5:0:
Density_comparison==add_neighbours && Extension_comparison==insufficient && Type_of_mobility==controlled && Energy_level==low && Target_application==emergency_situation? Sensor_behaviour==Sensor_mobility_x_extension? 0.5: Sensor_behaviour==Sensor_mobility_x_density? 0.5:0:
Density_comparison==add_neighbours && Extension_comparison==insufficient && Type_of_mobility==controlled && Energy_level==low && Target_application==emergency_situation ? Sensor_behaviour==Sensor_mobility_x_extension? 0.5: Sensor_behaviour==Sensor_mobility_x_density? 0.5:0:

Density_comparison==add_neighbours && Extension_comparison==insufficient && Type_of_mobility==controlled

&& Energy_level==low && Target_application==emergency_situation ? Sensor_behaviour==Sensor_mobility_x_extension? 0.5: Sensor_behaviour==Sensor_mobility_x_density? 0.5:0:0

Target application	Energy level	Type of mobility	Density comparison	Extension comparison	P (Sensor behaviour | Target applications, Energy level, Type of mobility, Density comparison, Extension comparison)				
					Mobility x extension	Mobility x density	Sleep x density	Deploy more sensors	Do not change behaviour
emergency situation	low	controlled	add neighbours	enough 100	0	1	0	0	0
				enough 95	0	1	0	0	0
				enough 90	0	1	0	0	0
				enough 85	0	1	0	0	0
				enough 80	0	1	0	0	0
				insufficient	0.5	0.5	0	0	0
			reduce neighbours	enough 100	0	0	1	0	0
				enough 95	0	0	1	0	0
				enough 90	0	0	1	0	0
				enough 85	0	0	1	0	0
				enough 80	0	0	0	0	1
				insufficient	1	0	0	0	0
			none	enough 100	0	0	0	0	1
				enough 95	0	0	0	0	1
				enough 90	0	0	0	0	1
				enough 85	0	0	0	0	1
				enough 80	0	0	0	0	1
				insufficient	1	0	0	0	0
		uncontrolled	add neighbours	enough 100	0	0	0	1	0
				enough 95	0	0	0	1	0
				enough 90	0	0	0	1	0
				enough 85	0	0	0	1	0
				enough 80	0	0	0	1	0
				insufficient	0	0	0	1	0
			reduce neighbours	enough 100	0	0	1	0	0
				enough 95	0	0	1	0	0
				enough 90	0	0	1	0	0
				enough 85	0	0	1	0	0
				enough 80	0	0	0	0	1
				insufficient	0	0	0	1	0
			none	enough 100	0	0	0	0	1
				enough 95	0	0	0	0	1
				enough 90	0	0	0	0	1
				enough 85	0	0	0	0	1
				enough 80	0	0	0	0	1
				insufficient	0	0	0	1	0
	high	controlled	add neighbours	enough 100	0	1	0	0	0
				enough 95	0	1	0	0	0
				enough 90	0	1	0	0	0
				enough 85	0	1	0	0	0
				enough 80	0	1	0	0	0
				insufficient	0.5	0.5	0	0	0

			reduce neighbours	enough 100	0	0	1	0	0
				enough 95	0	0	1	0	0
				enough 90	0	0	1	0	0
				enough 85	0	0	1	0	0
				enough 80	0	0	0	0	1
				insufficient	1	0	0	0	0
			none	enough 100	0	0	0	0	1
				enough 95	0	0	0	0	1
				enough 90	0	0	0	0	1
				enough 85	0	0	0	0	1
				enough 80	0	0	0	0	1
				insufficient	1	0	0	0	0
		uncontrolled	add neighbours	enough 100	0	0	0	1	0
				enough 95	0	0	0	1	0
				enough 90	0	0	0	1	0
				enough 85	0	0	0	1	0
				enough 80	0	0	0	1	0
				insufficient	0	0	0	1	0
			reduce neighbours	enough 100	0	0	1	0	0
				enough 95	0	0	1	0	0
				enough 90	0	0	1	0	0
				enough 85	0	0	1	0	0
				enough 80	0	0	0	0	1
				insufficient	0	0	0	1	0
			none	enough 100	0	0	0	0	1
				enough 95	0	0	0	0	1
				enough 90	0	0	0	0	1
				enough 85	0	0	0	0	1
				enough 80	0	0	0	0	1
				insufficient	0	0	0	1	0
normal situation	low	controlled	add neighbours	enough 100	0	0	0	1	0
				enough 95	0	0	0	1	0
				enough 90	0	0	0	1	0
				enough 85	0	0	0	1	0
				enough 80	0	0	0	1	0
				insufficient	0	0	0	1	0
			reduce neighbours	enough 100	0	0	1	0	0
				enough 95	0	0	1	0	0
				enough 90	0	0	1	0	0
				enough 85	0	0	1	0	0
				enough 80	0	0	0	0	1
				insufficient	0	0	0	1	0
			none	enough 100	0	0	0	0	1
				enough 95	0	0	0	0	1
				enough 90	0	0	0	0	1
				enough 85	0	0	0	0	1
				enough 80	0	0	0	0	1
				insufficient	0	0	0	1	0

		uncontrolled	add neighbours	enough 100	0	0	0	1	0
				enough 95	0	0	0	1	0
				enough 90	0	0	0	1	0
				enough 85	0	0	0	1	0
				enough 80	0	0	0	1	0
				insufficient	0	0	0	1	0
			reduce neighbours	enough 100	0	0	1	0	0
				enough 95	0	0	1	0	0
				enough 90	0	0	1	0	0
				enough 85	0	0	1	0	0
				enough 80	0	0	0	0	1
				insufficient	0	0	0	1	0
			none	enough 100	0	0	0	0	1
				enough 95	0	0	0	0	1
				enough 90	0	0	0	0	1
				enough 85	0	0	0	0	1
				enough 80	0	0	0	0	1
				insufficient	0	0	0	1	0
	high	controlled	add neighbours	enough 100	0	1	0	0	0
				enough 95	0	1	0	0	0
				enough 90	0	1	0	0	0
				enough 85	0	1	0	0	0
				enough 80	0	1	0	0	0
				insufficient	0.5	0.5	0	0	0
			reduce neighbours	enough 100	0	0	1	0	0
				enough 95	0	0	1	0	0
				enough 90	0	0	1	0	0
				enough 85	0	0	1	0	0
				enough 80	0	0	0	0	1
				insufficient	1	0	0	0	0
			none	enough 100	0	0	0	0	1
				enough 95	0	0	0	0	1
				enough 90	0	0	0	0	1
				enough 85	0	0	0	0	1
				enough 80	0	0	0	0	1
				insufficient	1	0	0	0	0
		uncontrolled	add neighbours	enough 100	0	0	0	1	0
				enough 95	0	0	0	1	0
				enough 90	0	0	0	1	0
				enough 85	0	0	0	1	0
				enough 80	0	0	0	1	0
				insufficient	0	0	0	1	0
			reduce neighbours	enough 100	0	0	1	0	0
				enough 95	0	0	1	0	0
				enough 90	0	0	1	0	0
				enough 85	0	0	1	0	0
				enough 80	0	0	0	0	1
				insufficient	0	0	0	1	0

			none	enough 100	0	0	0	0	1
				enough 95	0	0	0	0	1
				enough 90	0	0	0	0	1
				enough 85	0	0	0	0	1
				enough 80	0	0	0	0	1
				insufficient	0	0	0	1	0

Chapter 4

Value of information and mobility constraints for sampling with mobile sensors

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4.1. INTRODUCTION

The importance of environmental monitoring has been widely recognised for applications such as mapping of contaminants (Horsburgh *et al.*, 2010; Milton and Steed, 2007), levels of exposure to hazardous substances (Dubois *et al.*, 2011; Melles *et al.*, 2011) and species distribution (Zerger *et al.*, 2010). Rational decisions about natural resource management and emergency responses rely on information gathered by sensors. How these sensors are distributed affects sampling design (de Gruijter *et al.*, 2006) and, as a consequence, decision making. For instance, Heuvelink *et al.* (2010) illustrated the effect of sensor placement on dose predictions and decision making in a nuclear emergency situation. Erroneous predictions of an absence of radioactivity (false negatives) will lead to warnings not being triggered, whereas wrong predictions of the presence of radioactivity (false positives) will trigger unnecessary actions, such as the evacuation of residents and the deployment of rescue teams. The costs of prediction errors can be minimised by adapting spatial sampling to local variability.

Wireless sensor networks (WSNs) are increasingly used in environmental monitoring. They enable real-time monitoring with spatial and temporal resolutions never captured before (Nittel, 2009; Porter *et al.*, 2009; Rundel *et al.*, 2009; Zerger *et al.*, 2010). WSNs are composed of autonomous and wirelessly networked sensors spatially distributed in a study area (Akyildiz *et al.*, 2002). When using stationary WSNs, spatial sampling can be adapted to local variability by using sleeping and waking up mechanisms (Hefeeda and Bagheri, 2008; Willett *et al.*, 2004). This requires a high sensor density. However, mobile WSNs offer new opportunities to adapt spatial sampling using a reduced number of mobile sensors (Liu *et al.*, 2005; Rundel *et al.*, 2009; Singh *et al.*, 2006). Mobility is achieved by attaching sensors to mobile objects, such as robots (Dantu *et al.*, 2005), people (Campbell *et al.*, 2008), bicycles (Eisenman *et al.*, 2007), vehicles (Zoysa *et al.*, 2007) and animals (Juang *et al.*, 2002; Sahin, 2007). If mobility is controlled, the locations of sensors can be changed to achieve specific goals (Jun *et al.*, 2009), such as adapting sampling to local variability. In the paper, we consider the situation where the monitored phenomenon has a slower temporal rate as compared to the speed at which the sampling is done. More particularly, we assume that reality does not change during sampling. While this may seem a serious restriction, it is quite a common situation for example when assessing soil contamination (Rodriguez-Lado *et al.*, 2008; Romic *et al.*, 2007), natural radioactivity (Heuvelink and Griffith, 2010); and biodiversity (Zerger *et al.*, 2010).

When sampling with mobile sensors, two decisions have to be made: where the observation should be made, and which sensor should be moved to the location to make the observation. The first decision is to identify a sampling location to optimise a certain objective. The second decision is to choose a sensor to move to the identified location such that sensor mobility is efficiently managed.

Different approaches for deciding where to make the observation have been studied. Coverage-oriented approaches select locations according to geometric criteria, such as Voronoi diagrams and virtual forces (Wang *et al.*, 2009). Information-theoretic approaches (e.g. entropy and mutual information) seek to reduce uncertainty resulting from sensor mobility (Krause *et al.*, 2008). These approaches, however, have limitations. For example, they do not consider the phenomenon under investigation (Krause *et al.*, 2008; Walkowski, 2008), they do not identify misclassification types (false positives and false negatives) and they do not assess locations for their potential to minimise misclassifications (Donaldson-Matasci *et al.*, 2010).

An alternative approach is to use the expected value of information (EVoI). This method evaluates the expected relevance of observations made at certain locations, prior to making the observation (Bhattacharjya *et al.*, 2010; de Bruin *et al.*, 2001; Kangas, 2010). It compares the expected cost of making predictions using the available observations with the cost when an additional observation has been made in a new location. The EVoI is the reduction in the expected cost of prediction errors achieved by making the additional observation. The location of this additional observation can be selected by choosing the location that gives the highest EVoI. EVoI considers the phenomenon state and it allows decisions to be made based on the relevance of locations and different misclassification types. We therefore propose an EVoI maximisation criterion.

When deciding on which sensor to move to the new sample location, intuitively the best sensor would appear to be the closest one. However, constraints on the mobility of a sensor may make moving it costly or even impossible (Ballari *et al.*, 2012; Walkowski, 2008; Younis and Akkaya, 2008). These constraints may be hard or soft constraints. Hard mobility constraints make it impossible for the sensor to be moved: it may itself be immobile or movement may be obstructed by barriers between the current sensor location and that to be sampled. Soft mobility constraints include energy, terrain slope, speed, and sensor connectivity for data transmission. For example, moving up a slope is more costly than travelling downhill. In a previous study, sensors were selected using a weighted-distance approach (Verma *et al.*, 2006). Walkowski (2008) proposed the concepts of time geography to analyse constraints and select sensors within potential activity areas. Zou and Chakrabarty (2007) employed cost evaluation techniques to trade off target tracking improvements against mobility constraints.

Although these studies have integrated and prioritised mobility constraints, none of them have addressed their potential dependent influences. The influences of mobility constraints should not be considered independently of each other and may be dependent on the presence of other constraints. For instance, if sensors are carried by robots, battery status may affect both mobility and sensing capabilities, but if sensors are carried by people, battery status does not constrain mobility. The influence of sensor energy therefore depends on the type of mobile object. These dependencies should be taken into account because they can make influences of mobility constraints stronger, weaker or even inapplicable.

For deciding which sensor to move, we propose a cost-distance minimisation criterion that integrates mobility constraints with dependent influences. The cost-distance to move a sensor under mobility constraints is estimated using influence diagrams (IDs), a useful way to represent and make decisions (Howard and Matheson, 2005; Jensen and Nielsen, 2007; Kjaerulff and Madsen, 2007) Like decision trees, IDs link together the variables of a decision (i.e. factors, costs and decisions). The advantage of IDs over decision trees is that they provide a more compact representation of dependencies and more efficient computation when a high number of constraints are integrated (Varis, 1997).

This paper and the accompanying R script (R Development Core Team, 2010) illustrate a spatial sampling approach for use with mobile sensors that aims to maximise EVoI from new observations and minimise the cost-distance of sensor movement under mobility constraints. In the present study these two objectives are considered in separate steps.

First, we introduce EVoI, the calculation of misclassification costs, and the use of an aggregated EVoI. Then we describe the calculation of the cost-distance for moving a sensor under mobility constraints. A synthetic study case is described in section 4.4. Section 4.5 contains the results and discussions. Finally, conclusions are presented.

4.2. RELATED WORK

There is a substantial body of literature on mobile sensors and location selection. Surveys can be found in Wang *et al.* (2009), Wang *et al.* (2012), and Younis and Akkaya (2008). Several studies aim to select sensor locations to optimise network configuration, in terms of data transmission and connectivity (Ekici *et al.*, 2006) or energy conservation (Basagni *et al.*, 2008; Jain *et al.*, 2006; Wang *et al.*, 2010).

On the other hand, coverage-oriented approaches aim to select sensor locations in order to optimise spatial coverage of the study area. The coverage optimisation may be achieved by locating sensors at the centroids of k-means clusters (Walvoort *et al.*, 2010) or by using virtual forces which repel sensors from each other and from obstacles (Howard *et al.*, 2002) or Voronoi diagrams and Delaunay triangulation (Argany *et al.*, 2011). Similarly, in geostatistics the aim of sampling often is to minimise the (mean) kriging error variance (Brus and Heuvelink, 2007; Walkowski, 2008). The drawback of the above methods is that spatial sampling is adapted according to geometric criteria while it is not affected by characteristics of the monitored phenomenon.

Other approaches rely on ancillary data or covariates, such as digital elevation models, aerial or satellite imagery, and climate information, which are assumed to be correlated with the phenomenon of interest. For example, Minasny *et al.* (2007) used a quadtree method with secondary data to sparsely sampling in relatively uniform areas and more intensively where covariate variation is large. Minasny and McBratney (2006) used a Latin hypercube method to select locations that provide a full coverage of the range of each secondary variable. Brus and Heuvelink (2007) minimised the spatial average of the universal kriging variance to obtain the right balance between dispersing sensors in geographic and feature spaces. The applicability of these approaches, however, is restricted to the availability of ancillary data. For instance, they might not be available for the whole study area or with the required resolution, or they might be expensive to acquire.

Information-theoretic approaches employ entropy and mutual information to improve information quality by reducing uncertainty about the true state of the phenomenon (Krause *et al.*, 2008). These measures, however, do not depend on how data about the state of the phenomenon is used in decision making (Donaldson-Matasci *et al.*, 2010). They are measures of information quality, but they do not reflect the quality of the decision that will be made with sensor observations. In contrast, based on decision theory, our method considers both the network configuration and the information obtained from sensor observations. Decision-theory is concerned with (lack of) knowledge about the true state of a phenomenon and using this in rational decision making (Donaldson-Matasci *et al.*, 2010). For example, Heuvelink *et al.* (2010) and Melles *et al.* (2011) optimised the locations of mobile devices such that wrong decisions caused by false classifications were minimised. Our approach bears some similarity to this work, but it directly employs the concept of expected value of information (Bhattacharjya *et al.*, 2010; de Bruin *et al.*, 2001; Kangas, 2010) while it also considers sensor mobility constraints to minimise unwanted effects of sensor mobility on the WSN configuration itself, such as energy depletion. We did not come across other studies exploring the expected value of information for selecting mobile sensor locations.

4.3. METHODS

4.3.1. Value of information

The expected value of information (EVoI) is the difference between the prior and posterior costs of wrong predictions (Equation 4.1).

$$EVoI = E(C_{prior}) - E(C_{posterior}) \tag{4.1}$$

Consider a WSN with mobile sensors deployed in a study area. Sensors monitor at locations *l* a certain phenomenon (F) which, for simplicity, has either of two states (T): presence or absence. Prior information about the phenomenon is given by a set of discrete observations made by the sensors. These observations are interpolated to predict, at unobserved locations, the probability of the phenomenon being present P(f=present). This is called the prior probability map.

Using the prior probability map, unobserved locations are labelled as *phenomenon present* or *phenomenon absent*. To minimise misclassification costs, Bayes decision principle chooses the state with the minimum expected cost (Equation 4.2) (Berger, 1985). Let C(T,F) be the misclassification costs: $C_{wrong\text{-}p}$ for wrong predictions of phenomenon present, and $C_{wrong\text{-}a}$ for wrong predictions of phenomenon absent. There are no costs for correct predictions. The expected cost is based on available observations, thus it is called the prior expected cost of wrong predictions. Figure 4.1a illustrates this decision as a decision tree.

$$E(C_{prior}) = \min\left(C(T,F) * P(F_l) \right) \tag{4.2}$$

As the EVoI is evaluated before moving a sensor, Bayes theorem is used to update the prior probability P(F) into a posterior probability P(F|X), where X represents the new data. Because X has not been observed yet, the posterior probability P(F|X) is calculated from all possible outcomes of X (signals of presence and absence) and for all possible locations in the study area. In Equation 4.3, P(F) is the prior probability obtained using available observations at a considered location. P(X|F) is the likelihood of getting a presence signal if the phenomenon is actually present. Information about P(X|F) can be obtained from sensor sensitivity and specificity data in the sensor specifications. P(X) is the probability of getting a presence signal at the considered location. It is obtained by marginalising out the likelihood P(X|F) over the possible states of F.

$$P(F_l|X_l) = P(X|F) * P(F_l) / P(X_l) \quad ; \quad P(X_l) = \sum_F P(X|F) * P(F_l) \tag{4.3}$$

The posterior expected cost is calculated as in Equation 4.2, but using the posterior probability P(F|X) for all the possible outcomes of X (Equation 4.4). Following Bayes decision principle, the minimum expected costs of each outcome is weighted with P(X). This cost is calculated after updating the prior probability into a posterior one, thus it is called the posterior cost of wrong predictions. Figure 4.1b illustrates this decision as a decision tree. Figure 4.2 is an influence diagram for the decision tree shown in Figure 4.1.

$$E\left(C_{posterior}\right)=\sum_{X}P\left(X_l\right)*\min\left(C\left(T,F\right)*P\left(F_l|X_l\right)\right) \tag{4.4}$$

Finally, EVoI is calculated for each unobserved location using Equation 4.1. If E($C_{posterior}$) is smaller than E(C_{prior}), information has been gained and the misclassification cost reduced.

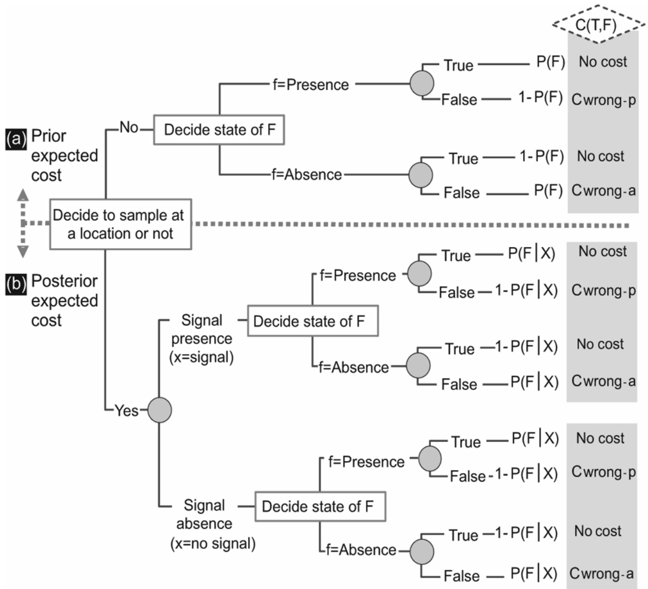

Figure 4.1. Decision tree for sampling a location: a) prior expected cost of wrong predictions; b) posterior expected cost of wrong predictions. Squares are decision nodes; circles are chance nodes. The grey column shows the misclassification costs assigned to each leaf of the decision tree.

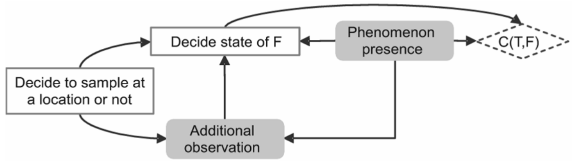

Figure 4.2. Influence diagram representing the decision tree in Figure 4.1.

Aggregated EVoI

The EVoI calculated as described above is called the *local EVoI*. However, spatial correlation between observations means that an observation carries information not only about its own location, but also about its vicinity. The expected reduction in misclassification costs aggregated over the whole study area is the *aggregated EVoI*. Maximising aggregated EVoI is equivalent to minimising misclassification costs over the whole study area.

Aggregated EVoI is calculated as the difference between the prior and posterior costs which have been aggregated over the whole map. A posterior probability map is predicted (interpolated) for each possible outcome of X and for each unobserved location. Then, for each posterior probability map, the posterior expected cost is calculated using Equation 4.4, and aggregated over the whole map. The location with the maximum aggregated EVoI is selected to be sampled.

4.3.2. Mobility constraints

The next step is to decide which sensor to move to the new location by calculating the cost-distances of moving each sensor. The sensor with the lowest cost-distance is selected.

We use influence diagrams (IDs) to integrate the mobility constraints into the calculation of cost-distances. An ID graphically represents the decision problem including the decision, factors and costs (Howard and Matheson, 2005; Jensen and Nielsen, 2007; Kjaerulff and Madsen, 2007).

The decision is whether to move a sensor or not. Factors are mobility constraints (MC) represented by sensor properties (i.e. energy, type of mobility, mobile object, speed, connectivity, etc.), a selected sensor trajectory and properties of the geographical space (i.e. barriers, slope, type of land use, etc.). Distance is also considered as a factor and depends on the selected sensor trajectory. Costs are the decision maker's preferences for each decision alternative, given the possible states of mobility constraints. Figure 4.3 shows the influence diagram with the decision as a square, factors as grey rounded squares, and the cost node as a diamond. The arrows pointing to the decision node are informational and represent the known information at the time of making the decision. The arrows pointing to the cost node are functional and represent the link between cost values and the underlying mobility constraints and the decision.

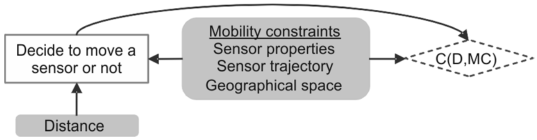

Figure 4.3. General influence diagram for deciding which sensor to move.

The cost-distance of moving a sensor (s) under mobility constraints is calculated using Equation 4.5, in which (d=move) is the decision to move the sensor. The cost values (C(d=move,MC)) are multiplied by the probability of mobility constraints being present (P(MC)) and the distance to travel (dist).

$$Cost\text{–}distance_s = dist_s * \left(C(d = move, MC_s) * P(MC_s) \right) \tag{4.5}$$

As it may be difficult to assess cost values in an integrated way when several mobility constraints are considered, costs are broken down by mobility constraints. However, the cost values of constraints with dependent influences need to be assessed together. This is shown on an ID where a cost node is shared by several constraints. The cost values for mobility constraints with independent influences are assessed individually. In an ID, this is shown where a cost node is linked to only one constraint. The joint cost is calculated by summing up the disaggregated costs multiplied by the Cartesian product of dependent mobility constraints (Bielza *et al.*, 2010). Equation 4.6 updates Equation 4.5 for the case of disaggregated costs. Finally, the sensor with the minimum cost-distance is selected as the one to move.

$$Cost\text{–}distance_s = dist_s * \left(\sum_{MC} C(d = move, MC_s) * \prod_{MC} P(MC_s) \right) \tag{4.6}$$

4.3.3. Comparison

To assess the performance of our proposed approach, its results were compared with those of a simple random approach in which sensors were selected on the basis of minimum Euclidian distance criterion. The sampling was repeated 100 times, with each repetition adding the same number of extra observations as in our approach. Moreover, both approaches started with the same sensor deployment. The resulting aggregated misclassification cost, accumulated travelled distance and accumulated cost-distance were compared with those obtained by our approach.

4.4. IMPLEMENTATION OF A SYNTHETIC CASE STUDY

A typical monitoring scenario with heterogeneous mobile sensors was illustrated using a synthetic dataset. EVoI and mobility constraints were simulated in R (R Development Core Team, 2010). We chose R because our method strongly depends on spatial interpolation such as implemented in the Gstat package

(Pebesma and Wesseling, 1998). The package sp was used for spatial data handling and visualisation (Pebesma and Bivand, 2005), and Gstat was used for geostatistical modelling, prediction and simulation. In addition, gRain was used to compute conditional probabilities used in influence diagrams (Højsgaard, 2009).

A synthetic dataset was constructed applying a threshold of 20 to a unconditional Gaussian random field of 120 x 120 grid cells, with a mean of 20, a nugget of 1 and a spherical structural spatial correlation component with a range of 40 and partial sill (semivariance) of 16. Presence was recorded for all cells whose realised value was above the threshold; otherwise absence was recorded (Figure 4.4a). Relative misclassification costs were set higher for false negatives than for false positives (cost values 3 and 2, respectively).

Initially, a WSN with 16 sensors was evenly deployed in the study area of 120 x 120 grid cells. Some sensors were assumed to be immobile; others were assumed to be mobile and carried by people, robots or bicycles. Table 4.1 shows the sensor metadata. For simplicity, metadata were assumed to be static during the simulation. The choice of this sensor network size was made to facilitate presentation and interpretation of results. Note that the examples given in the introduction require specialised (and thus expensive) sensors so that a WSN consisting of 16 sensors may be considered as realistic.

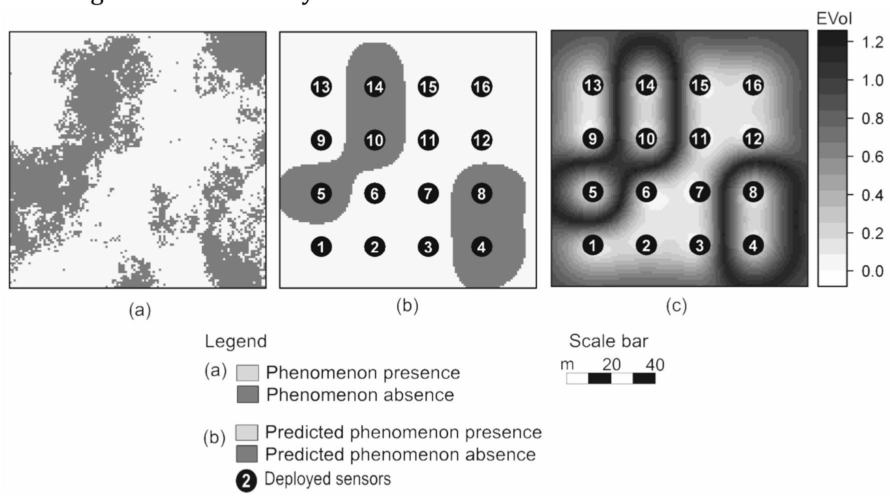

Figure 4.4. Implemented monitoring scenario with mobile sensors: a) simulated phenomenon; b) spatial interpolation and Bayes decision of initial sensor observations; c) local EVoI for initial observations. The numbers indicate the initial deployed sensors.

Table 4.1 Metadata of mobile sensors.

Sensor id	Mobile object	Type of mobility	Energy status
1	Pedestrian	Controlled	Low

2	Immobile	Immobile	High
3	Robot	Controlled	High
4	Robot	Controlled	High
5	Robot	Controlled	Low
6	Robot	Controlled	Low
7	Bicycle	Controlled	Low
8	Pedestrian	Controlled	High
9	Pedestrian	Controlled	Low
10	Immobile	Immobile	High
11	Immobile	Immobile	Low
12	Bicycle	Controlled	High
13	Robot	Controlled	High
14	Immobile	Immobile	High
15	Robot	Controlled	High
16	Pedestrian	Controlled	Low

4.4.1. Value of information

The sensors acquired initial observations at the locations by sampling the synthetic data. These observations were interpolated by indicator kriging using a spherical variogram with range=30 and sill=0.25. These parameter values should be interpreted as expert guesses, since initially there were too few data to estimate the variogram, while the true parameters of the generating process were unknown to the surveyor. Using the prior probability map, the phenomenon at each location was classified as either present or absent (Figure 4.4b). Note that the prior probability map was updated after each added observation.

Candidate locations were unobserved locations in the study area that can be occupied by a sensor. Obstacles, such as a river, cannot be occupied by a sensor, and were therefore excluded from the population of candidates. To speed up the simulation, exhaustive searching of candidates was restricted to locations having a local EVoI in the fourth quartile of the global distribution of EVoI (Figure 4.4c).

4.4.2. Mobility constraints

The influence diagram contained mobility constraints about sensor properties such as energy, mobile object, speed and type of mobility, as well as about the geographical space, such as barrier, terrain slope and land use type (Figure 4.5 and Table 4.2). For simplicity, the sensor trajectories were assumed to be straight. Individual cost nodes were created for the mobility constraints with independent influences (speed, land use and slope), and common cost nodes for those with dependent influences (energy and mobile object, type of mobility and barrier).

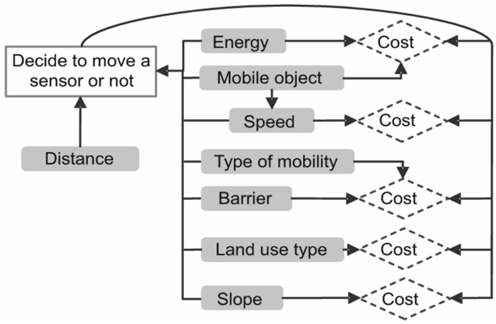

Figure 4.5. Influence diagram for deciding which sensor to move.

Table 4.2 Details about mobility constraints for deciding which sensor to move using the influence diagram shown in Figure 4.5.

Mobility constraints (Factor nodes)	Description	States	Deterministic or chance node	Data source
Distance	Topographic distance between a sensor and the selected location	no states	Deterministic	Coordinates of sensor location and selected location. Elevation map
Energy	Remaining sensor energy	low, high	Deterministic	Sensor metadata
Mobile object	Type of mobile object a sensor is attached to	pedestrian, robot, bicycle, car, robot, animal, immobile	Deterministic	Sensor metadata
Speed	Estimation of sensor speed depending on the type of mobile object	slow, medium, high, no speed	Chance	Sensor metadata (mobile object)
Type of mobility	Whether a sensor has controlled or uncontrolled mobility, or if it is immobile	controlled, uncontrolled, immobile	Deterministic	Sensor metadata
Barrier	Obstacles in the geographic space preventing sensor mobility (on sensor trajectory)	yes, no	Chance	Land use map
Land use type	Types of land uses on the sensor trajectory	forest, agriculture, residential, river	Chance	Land use map
Slope	Slope on the sensor trajectory	flat up, flat down, moderate up, moderate down, steep up, steep down, very steep up, very steep down	Chance	Elevation map

Probabilities of mobility constraints were computed using the sensor metadata in Table 4.1, and elevation and land use maps (Figure 4.6). The conditional probability of speed was determined according to the type of mobile object the sensor is attached to (Table 4.3). The probabilities were updated every time a new location to observe was selected.

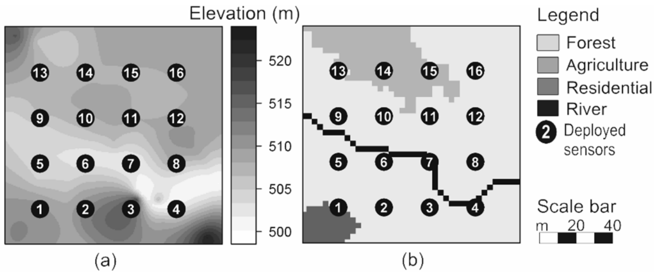

Figure 4.6. Study area: a) elevation; (b) land use.

Table 4.3 Conditional probability of speed per mobile object.

Mobile object	P(Speed | Mobile object)			
	Slow	Medium	High	No speed
Pedestrian	1	0	0	0
Robot	0.5	0.5	0	0
Bicycle	0.3	0.7	0	0
Car	0	0.1	0.9	0
Animal	0.4	0.3	0.3	0
Immobile	0	0	0	1

Two design choices were used to populate cost nodes. One design choice aimed to extend the WSN lifetime as much as possible by prioritising energy conservation. This represented monitoring in normal situations, i.e. without the occurrence of an emergency. The other design choice aimed to move a sensor as quickly as possible to a selected location by prioritising speed, regardless of energy consumption. This mimicked an emergency scenario. The cost values for soft constraints (energy, mobile object, speed, land use and slope) were assigned using a scale of 0 to 1, with 0 representing the least costly and 1 the most costly state. The scale was extended to 100 for recording values for hard constraints, such as barriers. This meant that excessively high costs were assigned to sensors with hard constraints to ensure they could not be selected. Tables with the cost values for both design choices are included in the Appendix B.

4.5. RESULTS AND DISCUSSION

4.5.1. Reducing the cost of making wrong predictions

The application results are presented in Figure 4.7. Figure 4.7a shows the selected location (i.e. the location with the maximum aggregated EVoI) for the first additional observation, using the initial set of observations. The selected sensor moved to this location and acquired an additional observation. Figure 4.7b shows the updated phenomenon map after this additional observation. Figure 4.7c shows the updated local EVoI. If there is no prior information, the mobile sensors can be used to make an initial sampling before starting the EVoI analysis.

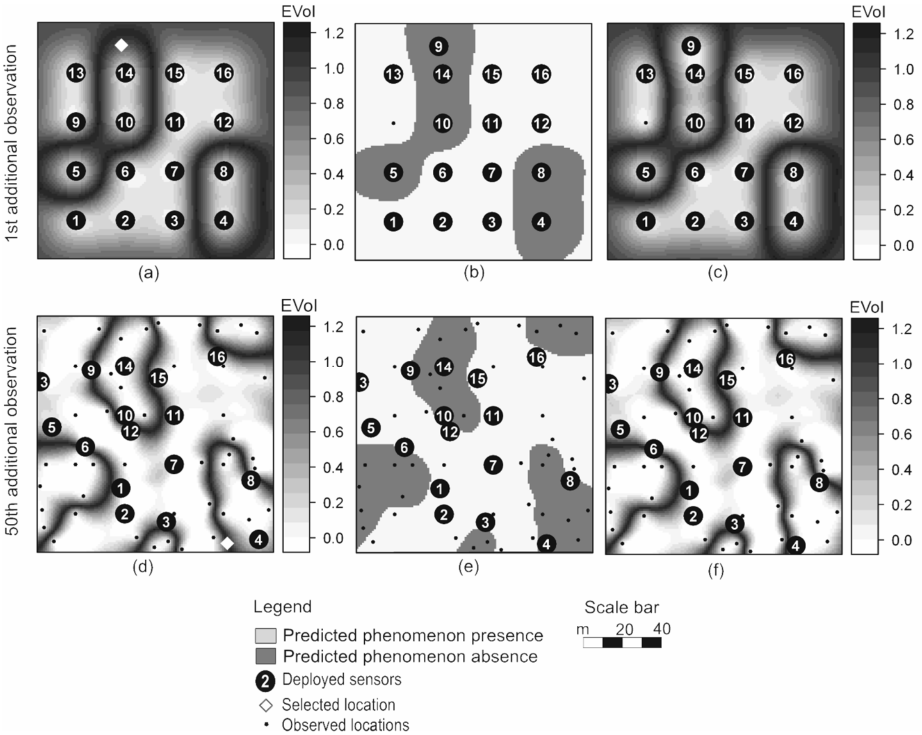

Figure 4.7. Application results of the EVoI analysis. First additional observation: a) selected location, background image shows local EVoI; b) updated phenomenon map; c) updated local EVoI. Fiftieth additional observation: d) selected location; e) updated phenomenon map; f) updated local EVoI.

The procedure was run to add 50 extra observations, one at a time. Observation of selected locations reduced misclassification costs while it improved the delineation of the phenomenon. Figures 4.7d to 4.7f show the selected location, the updated phenomenon map and the local EVoI for the fiftieth added observation. Note that the map in Figure 4.7f is much brighter than in Figure 4.7a. This indicates the achieved reduction in misclassification costs. The selected locations were usually located on the border between phenomenon states, which helped not only to reduce the cost of making wrong predictions, but also to better delineate the phenomenon.

Figure 4.8 shows the misclassification cost per additional observation as a percentage. By the fiftieth observation, the misclassification cost was reduced to 44.21%. Although the general trend was a reduction of the misclassification cost, certain locations turned out to be less valuable than expected. This was observed when the real cost (solid line) increased instead of falling. An example is the first additional observation. Although a cost reduction was expected, the result was an increase of 1.14%. Obviously, expected costs and realised costs may differ, but consistent divergence between the expected and actual values of information may be indicative of a misspecification of the geostatistical model. Once the sample is large enough (say, 100 observations) the indicator variogram can be estimated from the acquired data.

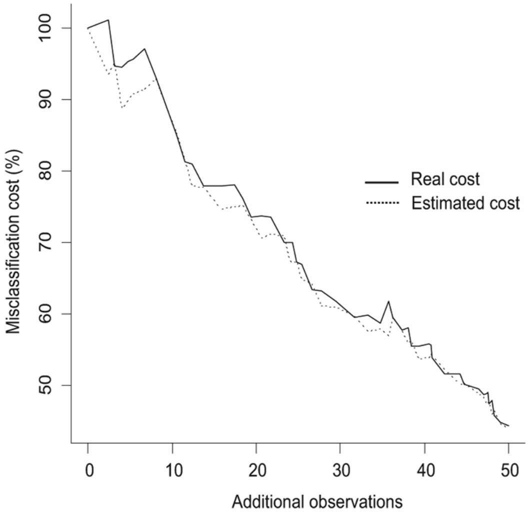

Figure 4.8. Misclassification cost per additional observation as a percentage.

We compared our results with those of a simple random selection approach. Figure 4.9 shows misclassification costs as percentages, in solid line for the 100 repetitions of the random selection, and in dashed line for the maximum aggregated EVoI criterion. Each of the 100 repetition added 50 extra observations and started with the same simulated phenomenon and sensor deployment as in the EVoI criterion. Each of the 100 repetitions of the random location selection produced larger misclassification costs than the aggregated EVoI criterion. The averaged misclassification cost for the random selection after the 100 repetitions was of 67.87% (standard deviation of 4.7%). Accordingly, our method performed significantly better than the selection of random locations (misclassification cost of 44.21% against 67.87%).

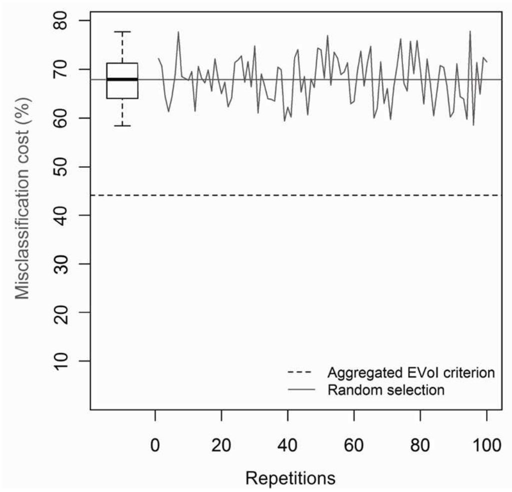

Figure 4.9. Comparison of maximum aggregated EVoI with a random selection approach. Aggregated misclassification cost per repetition is expressed as a percentage.

Note that in the current work we used exhaustive search over grid nodes to find the optimal next sensor location. This makes the procedure rather time demanding, but ensures that optima are found. For operational applications an optimiser should be considered. In addition, we accounted for the optimisation of single sensor movements at a time. Extending this to multiple sensor movements may require simultaneously evaluating several locations (Heuvelink *et al.*, 2010). Similarly, to support the observation of multiple locations on a sensor trajectory, such a trajectory should be optimised. This requires evaluating EVoI of intermediate locations as well as accounting for cost surfaces that may impede sensors to follow a specific trajectory or visit specific locations.

4.5.2. Sensor selection

Figure 4.10 shows the sensor selection for the first additional observation using the energy conserving design choice. Figure 4.10a shows the spatial distribution of sensors. The sensor with the minimum cost-distance (see grey bars in Figure 4.10b) was sensor 9 which was attached to a pedestrian and located at a distance of 44.76 m. This was the sensor selected to move.

Accounting for cost-distances thus prevents the selection of sensors with high movement costs even if they are located close to the new sampled location. Note that, in the example, the closest sensor was sensor 14 (see white bars in Figure 4.10b). However, this sensor was immobile, which imposed a hard mobility constraint. This can be seen in Figure 4.10c, which shows the influences broken down per mobility constraint. Other sensors were also impeded by hard mobility constraints; sensors 10 and 11 were immobile and sensors 1 to 7 had the river as a barrier. Sensors 13 and 15 were closer to the selected location than sensor 9, but their cost-distances were larger because they were attached to robots with a low energy reserve. This made their mobility costly. Energy was of no consequence for sensor 9 because it was attached to a pedestrian. The influences of slope and land use were similar for all sensors. Speed was unimportant given the design choice.

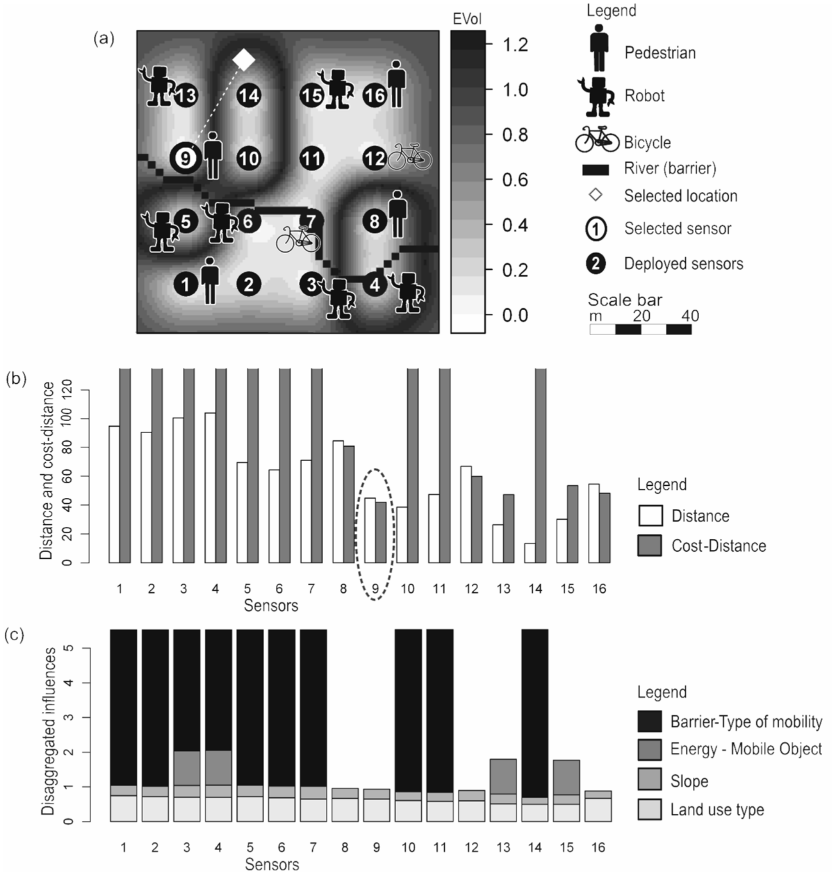

Figure 4.10. Sensor selection for the first additional observation in the energy conserving design choice: a) spatial distribution of sensors; b) distance and cost-distance per sensor; c) disaggregated influences of mobility constraints.

Different decision maker preferences can be encoded in the influence diagram through assigning different costs values to mobility constrains being present. This leads to different sensor selection which may be relevant for multi-purpose WSNs. For instance, Figure 4.11 shows the sensor selection in the emergency scenario. The selected sensor turned out to be sensor 13 instead of sensor 9. The reason for this is that speed imposed a larger cost on sensor 9 than sensor 13 since it was assumed that a robot could move faster than a pedestrian. Energy conservation was not considered in this scenario.

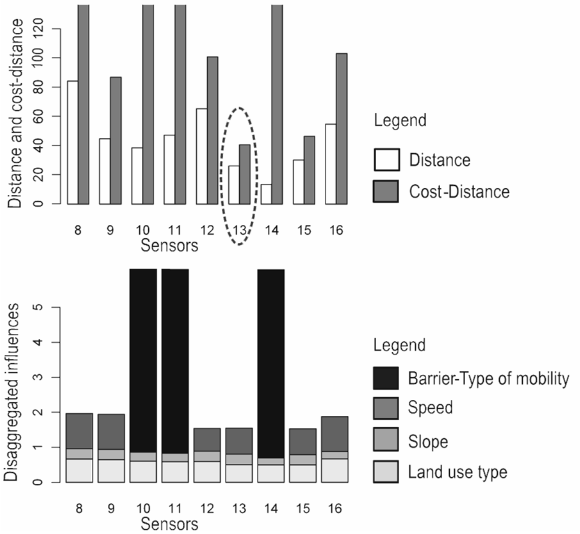

Figure 4.11. Sensor selection for the first additional observation in the design choice of observing the selected location as soon as possible.

We compared our results with those of selecting sensors with minimum Euclidian distance (Figure 4.12). Figure 4.12a shows the accumulated distance, in solid line for the minimum Euclidian distance criterion and in dashed line for the minimum cost-distance criterion. As expected, the accumulated distance was smaller for the Euclidian distance criterion than for the cost-distance criterion (an average of 663.08 m against 934.04 m). Figure 4.12b shows the accumulated cost-distance. It can be observed that the accumulated cost-distance was larger for the minimum Euclidian distance than for the minimum cost-distance (an average of 20698.39 against 1229.70). Although in our approach sensors traversed longer distances (41% more than the minimum Euclidian distance), they achieved a significantly lower cost-distance (94% less than the minimum Euclidian distance). Accordingly, our method performed significantly better than selecting sensors on the basis of minimum Euclidian distance. This result could be improved even more if accounting for least cost paths in the sensor selection procedure.

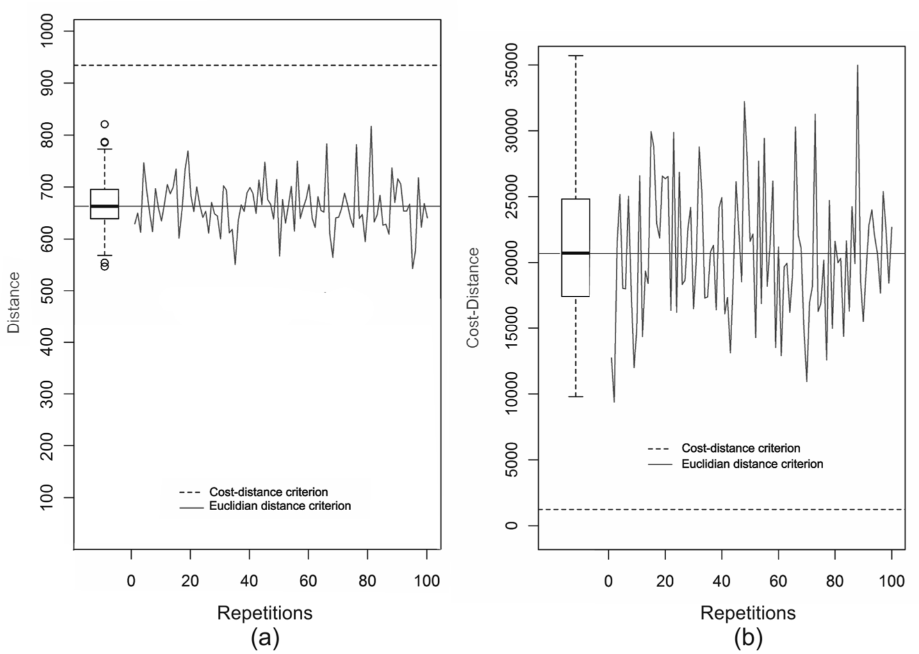

Figure 4.12. Comparison of cost-distance with minimum Euclidian distance: a) accumulated distance per repetition of the random approach in which sensors were selected on the basis of minimum Euclidian distance; b) accumulated cost-distance.

4.6. CONCLUSIONS

This paper presents an adaptive spatial sampling approach for use with mobile sensor networks. Two decisions were addressed: where should the additional sample be made and which sensor should be moved to the new sampling location? To select the sample location, we calculated the aggregated expected value of information (EVoI). To select the sensor to be moved, we used the cost-distances of sensors under hard and soft mobility constraints. The approach was demonstrated using a synthetic dataset and compared with a random location selection in which sensors were selected using a minimum Euclidian distance criterion. It demonstrated that sound locations were selected and their observations significantly reduced misclassification costs in comparison to the random approach while improving phenomenon delineation. Moreover, accounting for cost-distances significantly avoided costly sensor movements.

The advantage of using EVoI is that it takes into account the state of the phenomenon in the selected set of locations. In other words, the method is data dependent, which makes sense in many real-life situations, such as exposure to contaminants (Milton and Steed, 2007) and radioactivity (Melles *et al.*, 2011) or biodiversity assessment (Zerger *et al.*, 2010). Moreover, it distinguishes between costs associated with false positives and false negatives. This is especially useful in applications such as radioactivity, contaminants and fire risk, in which false negative costs are usually higher than false positives (Heuvelink *et al.*, 2010).

The method as presented in this paper applies to phenomena that change much slower than the speed of sampling, which is a common situation in phenomena such as soil contamination (Rodriguez-Lado *et al.*, 2008; Romic *et al.*, 2007), natural radioactivity (Heuvelink and Griffith, 2010); and biodiversity (Zerger *et al.*, 2010). Extending the method to highly dynamic phenomena requires considering the temporal behaviour of the phenomenon studied within the sampling procedure (Kho *et al.*, 2009), which is topic of further research.

Appendix B. Cost values for the implemented influence diagram

Table B1 Cost values for energy-mobile object (dependent and soft mobility constraints).

Energy	Mobile Object	C (d=move, Energy, Mobile object)	
		Design choice: prolong WSN lifetime	Design choice: observe the location as soon as possible
Low	Pedestrian	0	0
Low	Robot	1	0
Low	Bicycle	0	0
Low	Car	0	0
Low	Animal	0	0
Low	Immobile	0	0
High	Pedestrian	0	0
High	Robot	0	0
High	Bicycle	0	0
High	Car	0	0
High	Animal	0	0
High	Immobile	0	0

Table B2 Cost values for speed (independent and soft mobility constraint).

Speed	C (d=move, Speed)	
	Design choice: prolong WSN lifetime	Design choice: observe the location as soon as possible
Low	0	1
Medium	0	0.5
High	0	0
No speed	0	0

Table B3 Cost values for type of mobility and barrier (dependent and hard mobility constraints).

Type of mobility	Barrier	C (d=move, Type of mobility, Barrier)
		Design choice: prolong WSN lifetime = Design choice: observe the location as soon as possible
Controlled	yes	100
Controlled	no	0
Uncontrolled	yes	100
Uncontrolled	no	100
Static	yes	100
Static	no	100

Table B4 Cost values for land use type (independent and soft mobility constraint).

Land use type	C(d=move, Land use type)
	Design choice: prolong WSN lifetime = Design choice: observe the location as soon as possible
Residential	0.2
Agriculture	0.5
Forest	0.8
River	1

Table B5 Cost values for slope (independent and soft mobility constraint).

Slope	C (d=move, Slope, Direction)
	Design choice: prolong WSN lifetime = Design choice: observe the location as soon as possible
Flat up slope	0.2
Flat down slope	0.1
Moderate up slope	0.5
Moderate down slope	0.2
Steep up slope	0.8
Steep down slope	0.3
Very steep up slope	1
Very steep down slope	0.4

Chapter 5

Expected value of information for sampling dynamic phenomena with mobile sensors

Ballari, D., de Bruin, S., Bregt, A. K. (*under review*). Expected value of information for sampling dynamic phenomena with mobile sensors. International Journal of Applied Earth Observation and Geoinformation.

5.1. INTRODUCTION

Many environmental phenomena are dynamic in space and time (Heuvelink and Griffith, 2010). For example, owing to atmospheric conditions and the nature of the phenomena, polluted air, radioactivity, volcanic ash, chemical and smoke plumes vary in space as well as over time. Models accounting for such dynamics are essential to support decision making in the case of hazards and emergencies (Brenning and Dubois, 2008). Consider, for example, a scenario in which a fire releases polluted smoke into the open air. The smoke forms a plume that moves through space under the influence of wind speed and direction. Close to the fire source, there may be cropped fields. Knowing whether those fields are actually affected by the plume is critical. Pollutant concentrations can be predicted reasonably well by physical dispersion models. However, uncertainties in meteorological conditions and errors in the models themselves are propagated to the outputs. As result, model predictions will differ from reality (Heuvelink *et al.*, 2010). False negative predictions about pollutant concentrations exceeding a threshold may result in contaminated food entering the market, while false positive predictions may lead to the elimination of crops that are actually safe for consumption. The costs of these misclassifications can be minimised by using ground sensor observations to adjust the model predictions.

Wireless sensor networks (WSNs) are increasingly used to provide ground observations. They monitor the environment in real time with spatial and temporal resolutions never captured before (Nittel, 2009; Porter *et al.*, 2009; Rundel *et al.*, 2009; Zerger *et al.*, 2010). WSNs are composed of autonomous and wirelessly networked sensors that are spatially distributed throughout a study area (Akyildiz *et al.*, 2002). The main challenges of WSNs are related to overcoming their unique constraints, such as the limited life of low-power batteries, the short range of radio-based communication, and their limited storage capacity (Nittel, 2009). Sensors become mobile when they are attached to mobile objects, such as robots (Dantu *et al.*, 2005), people (Campbell *et al.*, 2008), bicycles (Eisenman *et al.*, 2007) and buses (Zoysa *et al.*, 2007). Mobility offers the opportunity to make ground observations at new locations by moving sensors (Liu *et al.*, 2005; Rundel *et al.*, 2009; Singh *et al.*, 2006). This is especially useful when the monitored phenomenon varies in space and time.

To obtain the maximum benefit from ground observations, sensor mobility needs to be optimised. Optimisation consists of deciding the best location to be observed by a mobile sensor at a certain point in time. Different approaches have been developed.

Coverage-oriented approaches select locations according to geometric criteria. Examples are Voronoi diagram and Delaunay triangulation, which identify sensing holes and create an optimal sensor deployment that minimises the sizes of the holes (Argany *et al.*, 2011), virtual forces which repel sensors from each other and from obstacles such that the deployed sensors spread out to maximise the covered area (Howard *et al.*, 2002), and calculating k-means clusters and deploying the sensors at the centroids of these clusters (Walvoort *et al.*, 2010). Similarly, geostatistical approaches may aim to minimise the mean kriging error variance (Brus and Heuvelink, 2007; Walkowski, 2008). These approaches select the locations to be observed according to geometric criteria without taking account of the characteristics of the monitored phenomenon.

Information-theoretic approaches employ entropy, mutual information and the Fisher information matrix to reduce uncertainty about the true state of the phenomenon (Krause *et al.*, 2008; Xu and Choi, 2011). These are measures of information quality, but they do not take any account of the quality of the decision to be made using sensor observations. In other words, they do not depend on how data about the state of the phenomenon is used in the decision-making process (Donaldson-Matasci *et al.*, 2010).

Other approaches use correlated data as prior information, such as digital elevation models, aerial or satellite imagery, climate information and dispersion models. For example, Minasny et al. (2007) used a quadtree method with secondary data to sparsely sample in relatively uniform areas and sample more intensively where covariate variation is large. Minasny and McBratney (2006) used a Latin hypercube method to select locations that provide a full coverage of the range of each secondary variable. Brus and Heuvelink (2007) minimised the spatial average of the universal kriging variance to obtain the right balance between dispersing sensors in geographical and feature spaces. These have the advantage of spreading observations not only in the geographical space, but also in the feature space. However, like information-theoretic approaches, these approaches do not depend on how data about the state of the phenomenon are used in decision making.

An alternative approach which overcomes these limitations is to use the expected value of information (EVoI). This is a decision-theory measure that concerns about the knowledge about the true state of a phenomenon (or the lack of it) and using this in rational decision making (Donaldson-Matasci *et al.*, 2010). Prior to making the observation, it evaluates the expected relevance of observing a certain location in time (Bhattacharjya *et al.*, 2010; de Bruin *et al.*, 2001; de Bruin and Hunter, 2003; Kangas, 2010). The EVoI compares the expected misclassification costs from a previous sensor deployment with that obtained from a new deployment in which one or more sensors are moved to a new location. The EVoI is the reduction in the expected misclassification cost achieved by the new deployment.

The objective of this paper is to contribute to the development of a methodology for deciding where to make ground observations over time to monitor a dynamic phenomenon using mobile sensors. First, the state of the phenomenon at each time step is modelled using regression kriging, which comprises logistic regression to handle prior information from a deterministic model and spatiotemporal kriging to handle stochastic residuals. Then an optimisation criterion is proposed which maximises the EVoI from a new sensor deployment at each time step. A two-stage approach is used. First, each sensor is set to its mobile mode (if possible) and the location with the maximum EVoI is computed for that sensor; in other words, a sensor-location association is made. Second, from all the individual sensor-location associations, the location with the greatest maximum value of information is chosen to be sampled by its associated sensor.

5.2. METHOD

The method is described by first introducing the calculation of the probability that a dynamic phenomenon exceeds a threshold. Second, the EVoI as optimisation criterion is presented. Figure 5.1 illustrates the main steps of the method.

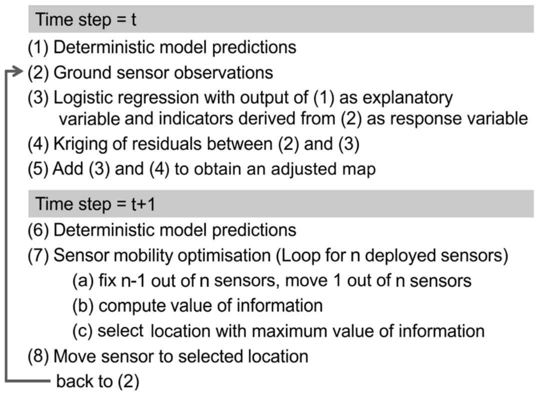

Figure 5.1. Main steps of the method.

5.2.1. Probability of exceeding a threshold

The probability of a pollutant Z at a location in space x and time t to be above an intervention level is modelled as the sum of a trend m and an error residual ε (Equation 5.1) (Heuvelink and Griffith, 2010; Heuvelink *et al.*, 2010; Kyriakidis and Journel, 1999). The probability is computed using regression indicator kriging which consists of logistic regression and spatiotemporal kriging (Hengl, 2009; Lin *et al.*, 2011). Figure 5.2 is a schematic representation of the steps described below.

$$P(z_{x,t} > threshold\ ) = m_{x,t} + \varepsilon_{x,t} \tag{5.1}$$

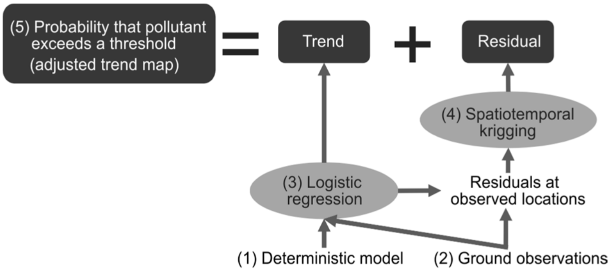

Figure 5.2. Elements for the calculation of the phenomenon probability of exceeding a threshold. Numbers correspond with the main steps in Figure 5.1.

The trend $m_{x,t}$ is obtained by logistic regression using the output of a deterministic model which could proceed from, for instance, remote sensing or pollutant dispersion models. Logistic regression records concentration values of the deterministic model (explanatory variable) as proportional values between 0 and 1 (response variable) (Hosmer and Lemeshow, 2000). The relationship between the explanatory and the response variables is expressed in Equation 5.2, with $m_{x,t}$ as the probability that the deterministic model output exceeds the threshold, B_0 and B_1 as the estimated coefficients for the logistic model, and $c_{x,t}$ as the concentration value at a location in space and time. The coefficients are fitted by using ground sensor observations expressed as a binomial variable.

$$\begin{aligned} &logit(m_{x,t}) = ln(m_{x,t} / 1 - m_{x,t}) = B_0 + B_1 c_{x,t} \\ &m_{x,t} = 1 \Big/ \left(1 + e^{-logit(m_{x,t})}\right) \end{aligned} \qquad (5.2)$$

The stochastic residuals $\varepsilon_{x,t}$ result from uncertainties in trend inputs and errors in models themselves that make model predictions differ from reality (Heuvelink *et al.*, 2010). They can be modelled by a spatiotemporally correlated field that is characterised by a spatiotemporal variogram. This may be modelled as a sum-metric spatiotemporal variogram, which is composed of a spatial variogram, a temporal variogram and a spatiotemporal variogram (Heuvelink and Griffith, 2010; Myers, 2004).

Although no residual data are directly available, ground sensor observations help to calculate them. Sensors observe the true state of the phenomenon, which is expressed as a binomial variable: *above threshold* or *below threshold*. Residuals at observed locations are the difference between the binomial observations and the probabilities obtained from the regression model. These differences are interpolated, using indicator kriging with zero mean and the spatiotemporal variogram, to predict residuals over the study area. Interpolated residuals are added to the regression output to obtain an adjusted trend map with the probability that a threshold is exceeded. This adjusted map shows a closer representation of reality than the original deterministic model, which does not comprise residuals.

5.2.2. Expected value of information

At each time step that the output of the deterministic model is updated, ground observations need to be made in order calculate residuals and adjust the trend. Before making such observations, however, it is necessary to determine the best locations to be observed. The optimisation criterion to make such decisions is the maximisation of the EVoI at each time step, which is the difference between the expected misclassification costs from the previous sensor deployment and that from a new deployment in which one or more sensors have moved to new locations (Equation 5.3).

$$EVoI = E(C_{previous\ deployment}) - E(C_{new\ deployment}) \tag{5.3}$$

First, each mobile sensor is associated with the location with maximum EVoI. Then the sensor-location association with maximum EVoI is chosen. Calculation details are provided in the following section. Note that in this study we consider a single sensor movement per time step.

Expected misclassification costs

The adjusted trend map using ground observations (i.e. time step = t) is used to label unobserved locations as *above threshold* or *below threshold*. To minimise misclassification costs, Bayes decision principle chooses the state with the minimum expected cost (Berger, 1985). Let $P(z_{x,t} > \text{threshold})$ be the probability of a pollutant Z at a location in space x and time t to be above an intervention level. In addition, let C be the misclassification costs: $C_{false\text{-}positive}$ for wrong predictions of the pollutant exceeding the threshold, and $C_{false\text{-}negative}$ for wrong predictions of the pollutant not exceeding the threshold. There are no costs for correct predictions. The expected misclassification cost at location x in time t, given a sensor deployment, is calculated by Equation 5.4. Figure 5.3 illustrates this decision as a decision tree.

$$E(C_{x,t}) = \min \left[C \times P(z_{x,t} > threshold) \right] \tag{5.4}$$

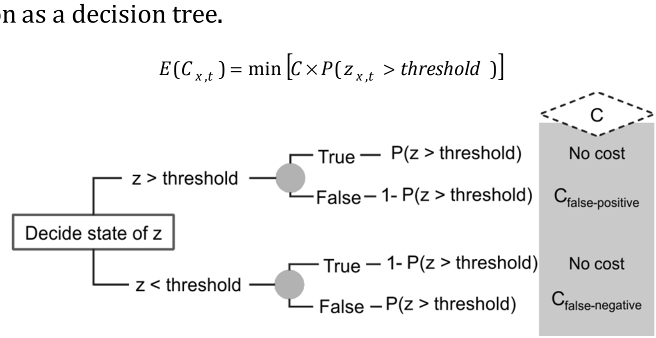

Figure 5.3. Decision tree to label the adjusted trend map as above threshold or below threshold.

When the output of the deterministic model is updated at a new time step (i.e. time step = t+1), misclassification costs cannot be calculated in a straightforward way as explained above. The reason is that observations cannot be made until a new sensor deployment has been decided. In such cases, the expected misclassification costs are computed as follows.

The expected misclassification cost from the previous sensor deployment $E(C_{previous\ deployment})$ relies on residuals of the previous time step, for which observations have been made. Spatiotemporal kriging interpolation, with zero mean, predicts residuals at the new time step using those of the previous time step and the sum-metric spatiotemporal variogram. With the predicted residuals, the current trend is adjusted and the misclassification cost is calculated using Equation 5.4.

However, the expected misclassification cost of a new sensor deployment $E(C_{new\ deployment})$ relies on the simulation that a sensor moves to a new location while other sensors remain immobile. Because observations have not been made yet, many realities are possible and so the possible combinations of sensor outcomes for the mobile and immobile sensors are simulated. Sensor outcomes are assumed to be spatially dependent, thus their joint conditional probability $P(s_1,\ldots,s_n)$ is calculated by recursively adding one new sensor outcome at a time (Equation 5.5). In Equation 5.5, $s_1,\ldots,s_{n-1}$ are the outcomes for the deployed sensors that remain immobile and s_n is the outcome for the sensor set to its mobile mode. The average cost of possible realities approximates the expected cost of the new deployment. The expected cost of the new deployment is obtained for each location in the study area and for each mobile sensor.

$$P(s_1,\ldots,s_n) = P(s_1,\ldots,s_{n-1}) \times P(s_n | s_1,\ldots,s_{n-1}) \tag{5.5}$$

The expected costs of the previous and new sensor deployments are aggregated over the study area (Equation 5.6). This accounts for local spatial variability, showing the value of the observation at a location not only for the observed location but also for its vicinity. It also shows the loss of information of no longer observing the location where the sensor is currently located.

$$Aggregated\ E(C) = \sum_x E(C_{x,t}) \tag{5.6}$$

Finally, EVoI is obtained by subtracting both aggregated expected costs from the previous sensor deployment and from the new deployment. The location with the maximum aggregated EVoI is selected for sampling by its associated mobile sensor. Maximising aggregated EVoI is equivalent to minimising misclassification costs over the whole study area.

5.3. IMPLEMENTATION OF A SYNTHETIC CASE STUDY

A synthetic dataset was used to illustrate a scenario in which a chemical factory burns and polluted smoke is released into the open air. The scenario was simulated in R (R Development Core Team, 2010). The package sp was used for spatial data handling and visualisation (Pebesma and Bivand, 2005), and Gstat was used for geostatistical modelling, prediction and simulation (Pebesma and Wesseling, 1998). In addition, lattice was used to visualise spatiotemporal data (Sarkar, 2008) and sampling as a support package for the simulation of sensor outcomes (Tillé and Matei, 2011).

A Gaussian plume model was used to calculate ground pollutant concentrations over a study area of 60 x 60 grid cells (Sutton, 1932). This deterministic plume was computed for 9 time steps. The plume varied in space and over time because of variations in wind speed and direction. Table 5.1 shows the input values for the Gaussian plume model at each time step. Figure 5.4a shows plume concentrations as outputs in micro-milligrams per cubic metre (μm/m^3) and illustrates how the plume spreads downwind. In time steps 1 to 6, the strong wind caused greater instability and bending of the plume. As a result, high ground concentrations were located close to the source. In time steps 7 to 9, however, the wind was slow, resulting in high ground concentrations further from the source.

Table 5.1 Inputs of Gaussian plume model for 9 time steps.

Time steps	Wind direction (azimuth)	Wind speed (m/s)	Other inputs
1	80	30	
2	60	25	Coordinates of source of emission: (0,0)
3	50	20	Ambient Temperature: 22 °C
4	20	20	Atmospheric condition: moderate unstable
5	10	10	Height of source of emission : 0 m
6	20	22	Diameter of emission: 1 m Emission rate: 10 g/s
7	35	9	Gas exit velocity: 5 m/s
8	30	7	Gas exit temperature: 200 °C
9	25	4	

Stochastic residuals with zero mean were constructed on a three-dimensional, unconditional Gaussian random field of 60 grid cells in x, 60 in y, and 9 in t. The third dimension t represented time. A sum-metric spatiotemporal variogram was used. The Gstat code for the spatiotemporal variogram is given in Equation 5.7. A maximum sill was set in order to explain the 20% of the variation of the deterministic plume: [0.2*mean(plume concentrations)]^2. The resulting stochastic residuals (Figure 5.4b) were added to the deterministic plume to obtain the true phenomenon concentration (Figure 5.4c). Finally, an arbitrary threshold of 30 µm/m3 was applied. Cells in which real pollution concentrations exceeded the threshold were recorded as *above threshold*; cells where real concentrations were below the threshold were recorded as *below threshold* (Figure 5.4d). This was the reality to be observed by sensors.

$$\begin{aligned}&\textit{Spatial variogram}\\&vgm.s = vgm(\max\ total\ sill/2, \text{"Sph"}, 50E6, anis = c(0,90,0,1E\text{-}6,1E\text{-}6))\\&\textit{Temporal variogram}\\&vgm.t = vgm(\max\ total\ sill/10, \text{"Sph"}, 10E6, anis = c(0,0,0,1,1E\text{-}6), add.to = vgm.s)\\&\textit{Spatiotemporal variogram}\\&vm = vgm(\max\ total\ sill/10, \text{"Sph"}, 60, anis = c(0,0,0,1,0.2), add.to = vgm.t)\end{aligned} \tag{5.7}$$

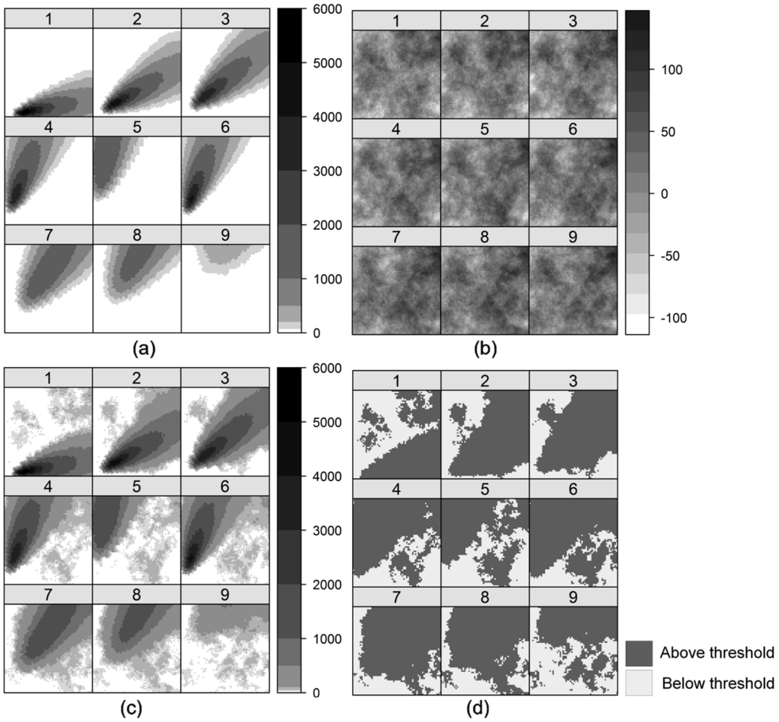

Figure 5.4. Illustration of a synthetic dynamic smoke plume over time: a) deterministic plume (ground concentrations); b) stochastic residual; c) reality = plume + residual; d) real concentrations exceeding the threshold. Figures a, b and c represent concentration values expressed in µm/m3.

Initially, a WSN with 9 sensors was evenly deployed in the study area of 60 x 60 grid cells (Figure 5.5). Some sensors were immobile; others were mobile and carried by people, robots or bikes. Table 5.2 shows the sensor metadata.

Table 5.2 Metadata of mobile sensors.

Sensor id	Mobile object	Type of mobility
1	Immobile	Immobile
2	Immobile	Immobile
3	Robot	Controlled
4	Robot	Controlled
5	Robot	Controlled
6	Immobile	Immobile
7	Immobile	Immobile
8	Bike	Controlled
9	Pedestrian	Controlled

Figure 5.5. Initial sensor deployment at the first time step with the observable reality as background.

5.3.1. Expected value of information

At the first time step (i.e. t=1), sensors acquired initial observations by sampling synthetic data. Observations with value 1 indicated that the threshold was exceeded, while value 0 indicated that the threshold was not exceeded. Regression kriging was used to obtain probabilities that the threshold was exceeded. Coefficients B_0 and B_1 of logistic regression (Equation 5.2) were fitted, making use of the ground observations and the *glm* and *predict* functions of the R Stats package (Manning, 2007). Residuals were calculated by subtracting the logistic regression output from observations and interpolated using indicator kriging with a sum-metric spatiotemporal variogram (Equation 5.8). The parameters of the spatiotemporal variogram should be interpreted as expert guesses, since initially there were too few data to estimate the variogram, while the true parameters of the generating process were unknown to the surveyor or investigator.

Spatial variogram (5.8)

vgm.s = vgm(0.1*, "Sph",* 30*E*6*,anis = c(* 0,90,0,1*E*-6,1*E*-6*))*

Temporal variogram

vgm.t = vgm(0.05*, "Sph",* 10*E*6*,anis = c(* 0,0,0,1,1*E*-6*), add.to = vgm.s)*

Spatiotemporal variogram

vm_model = vgm(0.05," Sph" , 40, anis = c(0,0,0,1,0.2), add.to = vgm.t)

The plume was adjusted using the interpolated residual map. The pollutant concentration at each location was classified as either above the threshold or below it. Misclassification costs were calculated, with the cost of a false negative set higher than the cost of a false positive (cost values 3 and 2). To speed up the simulation, exhaustive searching of candidate locations was restricted to locations having expected misclassification costs from the previous deployment in the fourth quartile of the global cost distribution. Locations closer than 3 cells to sensors were omitted to avoid moving sensors very close to other sensors. Finally, to calculate the average costs of possible realities, the most probable outcomes with a sum of probabilities approaching 0.75 were used.

5.3.2. Comparison

To assess our approach, the results were compared with results obtained using a simple random approach and results obtained from the previous deployment without performing any sensor movement. In the simple random approach, the locations and sensors were both randomly chosen. Candidate locations were restricted as explained above. When ground observations did not provide additional information (i.e. the aggregated absolute value of detected residuals at the observed locations were smaller than 0.2), such new deployments were not considered, because they could produce only very low misclassification costs. This, however, could not be considered as realistic, because no additional information was gained and thus the calculation of misclassification costs relied entirely on the deterministic plume. The sampling was repeated 100 times at each time step. The resulting misclassification costs at each time step were compared with those obtained by our approach.

5.4. RESULTS AND DISCUSSION

The overall results demonstrate that the proposed method helped to reduce risk caused by poor model predictions. This was achieved by optimising sensor mobility such that residuals were detected and misclassification cost reduced. The ‘A’ maps in Figure 5.6 are the adjusted plume maps with the detected residuals; the ‘B’ maps are the final classified maps showing the areas where pollutant concentrations exceed the threshold.

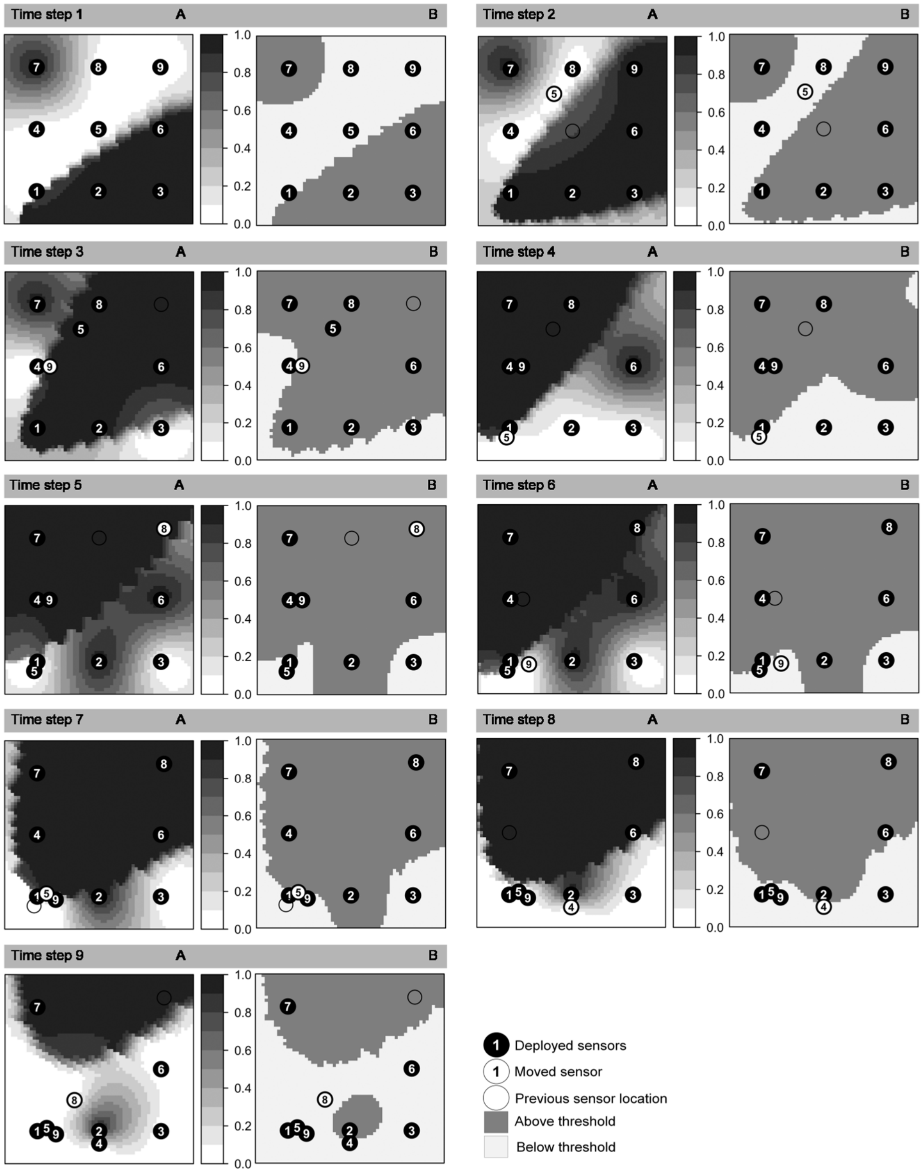

Figure 5.6. Resulting adjusted trend maps (A) and final classified maps (B) for each time step.

The adjusted maps (Figure 5.6 'A' maps) show the probability that the threshold was exceeded at each time step. The deterministic plume had a high probability of exceeding the threshold, and is shown in darker colours than the rest of the map. Detected residuals could increase the probability of exceeding the threshold (false negatives outside the plume), or reduce it (false positives inside the plume). Although the deterministic model explained much of the phenomenon behaviour, detected residuals were also important sources of information to improve predictions.

The final maps (Figure 5.6 'B' maps) show the classification of unobserved locations as either above or below the threshold. These maps delineate areas where pollution concentration exceeded the threshold at the different time steps. The classification relied on the original plume and on the detected false negatives and false positives. False positives proved to have less of an influence on the phenomenon delineation than false negatives. The reason for this is that the deterministic model explained much of the phenomenon behaviour where there was a high probability of exceeding the threshold (i.e. probability close to 1). The differences between the original plume and the ground observations therefore gave small false positive residuals, which in some cases were too small to effect any changes in the map. We added as many observations per time step as the number of deployed sensors. To obtain a more detailed map of the phenomenon, more observations per time step could be added by sequentially optimising sensor movements and considering that the deterministic plume remains static.

The moved sensors successfully detected residuals at every time step, except time step 5 (Figure 5.7). The movement in time step 5 proved to be less successful than expected. This could be attributed to misspecifications of the geostatistical and regression model, and to an insufficient number of selected outcomes to calculate the average costs of possible realities. The geostatistical model could be improved if estimated and adapted while new information is gathered using learning algorithms (Xu and Choi, 2011). According to Hengl (2009), the regression model could be improved by using a larger number of observations to fit the regression coefficients and ensuring that they efficiently represent the feature space. This, however, may require a dual optimisation of sensor mobility, because of the use of ground observations to fit the regression model and to calculate the residuals. Finally, consideration could be given to using a larger number of selected outcomes to calculate the average costs of possible realities. However, this would increase processing time because we used exhaustive search over grid nodes to find the optimal sensor location.

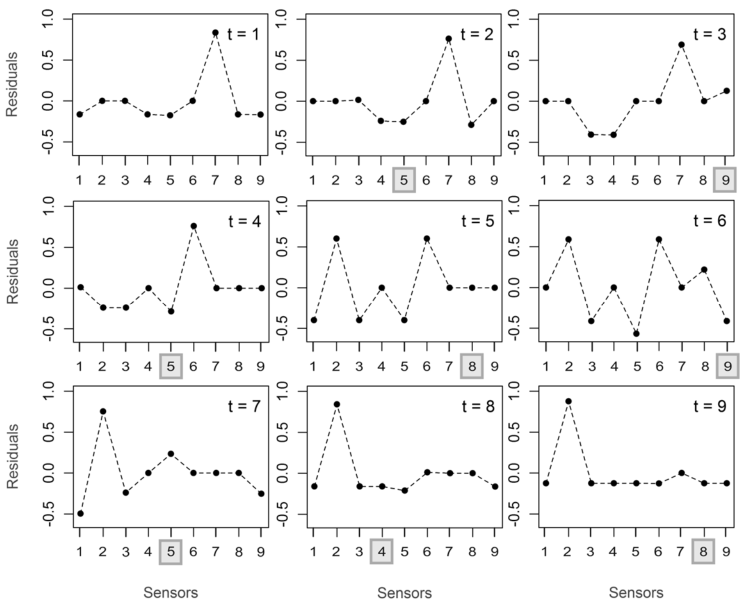

Figure 5.7. Detected residuals for each sensor and time step. The highlighted sensors are the ones moved. Positive values represent false negative residuals; negative values represent false positive residuals.

The achieved misclassification cost reduction from the aggregated EVoI criterion was compared with random sensor movements and with the previous deployment (i.e. without sensor movements). Table 5.3 and Figure 5.8 contain the results of the comparison with the random approach; Table 5.4 and Figure 5.9 contain the results of the comparison with the previous deployment. Note that misclassification cost reduction at different time steps cannot be compared because reality has changed from one time step to another. Instead, the misclassification cost reduction has to be compared within the same time step and between the different approaches (i.e. read table rows).

Table 5.3 compares the numerical results of the EVoI criterion and the random selection. It shows the achieved misclassifications costs at the different time steps, their difference as percentages, and the accumulated misclassification cost over time steps. The EVoI criterion produced smaller misclassification cost than the random approach at each time step, except in time steps 2 and 6 (Figure 5.8). On average, the EVoI criterion per time step performed 18% better than the random approach. The accumulated misclassification cost over the 9 time steps from the EVoI criterion was 14% smaller than that from the random approach (8393.63 and 9575.29 respectively). Accordingly, our method performed significantly better than the random approach (an averaged misclassification cost reduction per time step of 18% and an accumulated misclassification cost reduction of 14%).

Sensor movements that proved to be less informative than expected (i.e. in time steps 2 and 6) could be attributed, as discussed above, to misspecification of the geostatistical and regression model, and to an insufficient number of selected outcomes for the simulation of possible realities.

Table 5.3 Numerical results of misclassification costs from the EVoI criterion and the random criterion. Positives values mean that the EVoI criterion performed better than the random selection.

Time steps	Misclassification costs from EVoI criterion	Misclassification costs from random criterion	Difference in %	Accumulated misclassification costs from EVoI criterion	Accumulated misclassification costs from random criterion
1	917.30	917.30	0.00	917.30	917.30
2	1307.90	1227.28	-6.16	2225.20	2144.58
3	938.07	1134.20	+20.91	3163.27	3278.78
4	1033.02	1137.04	+10.07	4196.29	4415.82
5	1087.40	1427.46	+31.27	5283.69	5843.28
6	929.39	849.67	-8.58	6213.08	6692.95
7	621.45	845.22	+36.01	6834.52	7538.17
8	512.78	802.37	+56.47	7347.31	8340.53
9	1046.32	1234.76	+18.01	8393.63	9575.29
		Average	+17.56~+18%		

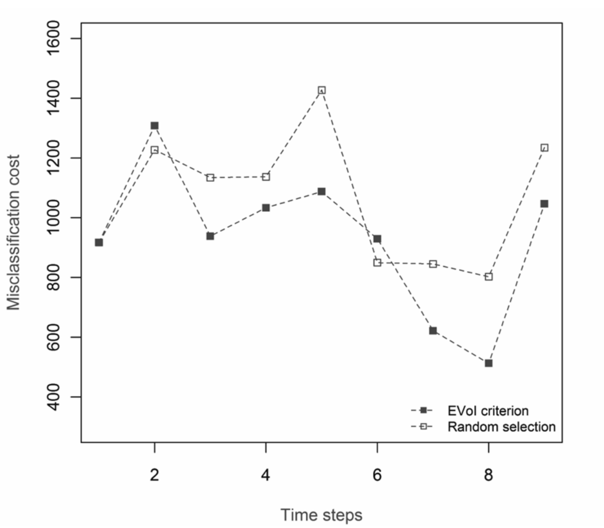

Figure 5.8. Comparison of misclassification costs from the EVoI criterion and random sensor movements.

Table 5.4 compares the numerical results obtained from the EVoI criterion and the previous deployment. The EVoI criterion produced smaller misclassification cost than the previous deployment at each time step, except in time steps 4 and 6 (Figure 5.9). On average, the EVoI criterion per time step performed 6% better than the previous deployment. The accumulated misclassification cost over the 9 time steps from the EVoI criterion was 3% smaller than that from the previous deployment (8393.63 and 8623.22 respectively). Accordingly, our method performed better than the previous deployment (an averaged misclassification cost reduction per time step of 6% and an accumulated misclassification cost reduction of 3%).

In time step 4 the misclassification cost from the previous deployment was very low (25.28). The misclassification cost relied entirely on the deterministic plume because sensors did not provide any additional information (i.e. detected residuals were very small). This resulted in very low misclassification cost, which could not be considered as realistic because no additional information was gained from ground observations.

Table 5.4 Numerical results of misclassification costs from the EVoI criterion and the previous deployment without any sensor movement. Positives values mean that the EVoI criterion performed better than the previous deployment.

Time steps	Misclassification costs from EVoI criterion	Misclassification costs from previous deployment	Difference in %	Accumulated misclassification costs from EVoI criterion	Accumulated misclassification costs from previous deployment
1	917.30	917.30	0.00	917.30	917.30
2	1307.90	1335.36	+2.10	2225.20	2252.65
3	938.07	1225.26	+30.62	3163.27	3477.91
4	1033.02	25.28	-97.55	4196.29	3503.19
5	1087.40	1498.42	+37.80	5283.69	5001.61
6	929.39	917.54	-1.28	6213.08	5919.15
7	621.45	819.70	+31.90	6834.52	6738.85
8	512.78	676.58	+31.94	7347.31	7415.43
9	1046.32	1207.79	+15.43	8393.63	8623.22
		Average	+5.66~+6		

Although our approach provided sound locations to reduce misclassification costs, the resulting spatial distribution of sensors could be criticised. Some sensors were moved long distances to be located close to other mobile sensors. The drawback of this is that long movements may consume a considerable amount of battery power and observation may be delayed. Therefore, mobility constraints such as sensor battery, terrain slope and distance to move could be used to select a suitable sensor to be moved to the selected location (Ballari *et al.*, 2012). A three-step approach could be considered: first, each sensor is set to its mobile mode and the location with maximum EVoI is computed for that sensor; second, the sensor-location association having the maximum EVoI is chosen; third, the sensor to be moved is reconsidered by accounting for mobility constraints. After observing its current location, the new selected sensor could be moved to the selected location. Further research is needed on such an approach.

Similar approaches to our work have been carried out by Heuvelink *et al.* (2010) and Melles *et al.* (2011). They optimised the locations of fixed and mobile devices such that wrong decisions caused by false classifications were minimised. Although our approach bears some similarity to their work, we directly employed the concept of expected value of information (Bhattacharjya *et al.*, 2010; de Bruin *et al.*, 2001; de Bruin and Hunter, 2003; Kangas, 2010). This allowed us to select locations to be sampled according to their relevance for improving the quality of the decisions to be made using the sensor observations.

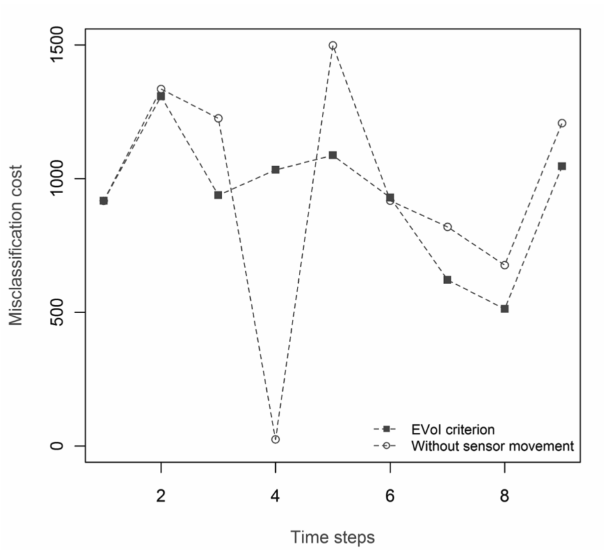

Figure 5.9. Comparison of misclassification costs from the EVoI criterion and previous sensor deployment without any sensor movement.

5.5. CONCLUSIONS

This paper presents a method for deciding where to make ground observations over time using mobile sensors, with the purpose of improving dynamic phenomenon prediction. This was done by optimising sensor mobility such that ground sensor observations reduced the risk caused by poor model predictions. The optimisation criterion used was maximisation of the expected value of information from a new sensor deployment at each time step. The approach was demonstrated using a synthetic dataset and compared with a random sensor and location selection approach and with the observation of the previous deployment without performing sensor movements. The results demonstrated that EVoI criterion selected sound locations where the observations made significantly reduced misclassification costs in comparison with the random approach and the previous deployment.

Our method requires prior information about the spatiotemporal trend of the dynamic phenomenon and the variogram of residuals. The former may be available from remote sensing images, physical dispersion models and national weather or radioactivity sensor networks. If no information is available for the variogram of residuals, the mobile sensors could collect information in an initial sampling phase or reconnaissance survey (Brus and Heuvelink, 2007).

Chapter 6

Synthesis

6.1. INTRODUCTION

Mobile sensor networks represent a new paradigm for environmental monitoring. But while they promise flexible and adaptable spatial sampling of the monitored phenomenon, limitations of sensor networks in terms of connectivity and energy depletion also limit the sensor mobility needed for this flexible and adaptable sampling. Within this context, the main goal of this thesis was to explore approaches for managing sensor mobility within a wireless sensor network (WSN) for use in environmental monitoring. To achieve this overall goal, four sub-objectives were defined:

1. Explore the use of metadata to describe the dynamic status of wireless sensor networks.
2. Develop a mobility constraint model to infer mobile sensor behaviour.
3. Develop a method to adapt spatial sampling using mobile, constrained sensors.
4. Extend the developed adaptive sampling method to monitoring highly dynamic environmental phenomena.

These objectives are revisited below in a discussion of the main findings and limitations, followed by a reflection on the results and suggestions for future research.

6.2. MAIN FINDINGS

6.2.1. Metadata

Wireless sensor networks are highly dynamic and changes in their status are therefore frequent. This thesis has shown that metadata are suitable for describing the status of and changes in WSNs, and reporting this information back to other components, systems or users (Ballari *et al.*, 2009). Metadata are descriptors of observed data, WSN configurations and functionalities, and even the situations in which monitoring is done. Some metadata, such as specifications of attached sensing devices, owners, security levels or access restrictions, are static and defined by sensor configurations. Other metadata, such as battery levels, sensor location, or sensor neighbours, are dynamic and should be automatically generated and updated to obtain a current status description of the WSN.

A context model was proposed to describe WSN status that is based on four types of contexts: sensor, network, sensing and organisation. In this model, metadata are used as parameters that describe what is happening in the different contexts. The advantage of this model is the possibility of performing contextualised decisions based on the current WSN status and the situation in which the monitoring is carried out.

6.2.2. Mobility constraints

Knowing how mobile sensors should behave in the presence of mobility constraints is an important step towards mobile monitoring. A model was developed to describe mobility constraints within the different types of WSN contexts: sensor, network, sensing and organisation (Ballari *et al.*, 2012). It consists of a context graph, modelled as a Bayesian network, which is fed with metadata values about the monitored phenomenon and sensor properties. Changes of status shown by metadata are propagated through the context graph and contextual rules used to infer the most suitable sensor behaviour. Such behaviour focused on achieving a suitable spatial coverage of the WSN when monitoring forest fire risk by sending sensors to sleep, moving them to enhance coverage density and extension, or deploying more sensors.

The model also describes, from sensor observations, the phenomenon state within the monitored area. It infers whether sensors should move, but it does not determine the precise locations where they should go. Similarly, the method does not address how adjustments provided by sensor behaviour could ultimately improve the phenomenon monitoring. Furthermore, the definition of mobility constraints in the context graph may be complex if a high number of constraints are involved and metadata values are not available due to cost or the impossibility of obtaining them. In this case, experts, with the help of knowledge elicitation methods, are needed to define contextual rules encoding the strengths of dependencies between mobility constraints (i.e. conditional probabilities). Although this model was developed for use in monitoring fire risk, it could also be used to describe mobility constraints and infer sensor behaviour for monitoring other environmental phenomena, such as air pollution, noise or soil moisture.

6.2.3. Spatial sampling

Two aspects of spatial sampling were addressed: which location should be sampled and which mobile sensor should move to that location? A form of adaptive sampling by mobile sensors was proposed according to the expected value of information (EVoI) and mobility constraints (Ballari *et al.*, under review). EVoI allows decisions to be made about the location to be observed. A spatially aggregated EVoI criterion is used to minimise the expected costs of wrong predictions about a phenomenon. Mobility constraints allow decisions to be made about which sensor to move. A cost-distance criterion is used to minimise unwanted effects of sensor mobility on the WSN itself, such as energy depletion.

The method was assessed by comparing it with a random selection of sample locations and sensor selection based on a minimum Euclidian distance criterion. This demonstrated that the EVoI approach selects sound locations which deliver observations that significantly reduce prediction errors in comparison with the random approach. Such observations also improve phenomenon delineation. Moreover, accounting for cost-distances significantly avoided costly sensor movements, although sensors may move longer distances than in the minimum Euclidian distance criterion.

This method also has some limitations. It can only be used to monitor phenomena that change at a much slower rate than the speed of sampling. Suitable phenomena therefore have slow temporal dynamics, such as soil contamination, natural radioactivity and biodiversity. Moreover, the method optimises a single sensor movement at a time, and a single observation per sensor movement.

6.2.4. Spatiotemporal sampling of dynamic phenomena

A dynamic environmental phenomenon was considered in a scenario in which a fire in a chemical factory released polluted smoke into the open air. The plume varied in space and time because of variations in atmospheric conditions and could only be partially predicted by a deterministic dispersion model. The scenario explored the use of in-situ observations acquired by mobile sensors to improve predictions.

A method was developed for deciding when and where to sample the dynamic phenomenon using mobile sensors (Ballari *et al.*, in preparation). The method first accounts for the state of the phenomenon at a time step and then optimises an objective function. The probability of the phenomenon (i.e. polluted smoke) exceeding a threshold at a time step is modelled using regression indicator kriging. Logistic regression is used to handle the deterministic dispersion model component and spatiotemporal kriging is used to handle stochastic residuals. The optimisation criterion is the maximisation of the EVoI from a new sensor deployment at each time step.

The method was assessed by comparing it with a random sensor and location selection approach and with the observation of the previous deployment without performing any sensor movement. The results demonstrated that the EVoI criterion selected sound locations where the observations helped to detect residuals and successfully reduce risk caused by poor model predictions. The EVoI criterion significantly reduced misclassification costs in comparison with the random approach and the previous deployment.

However, this method also has some limitations. The resulting spatial distribution of sensors could be criticised. Some sensors moved long distances to be located close to other mobile sensors. This consumed a considerable amount of battery power while observation was delayed. Therefore, mobility constraints could be useful for selecting suitable sensors to be moved once the sampled locations have been selected. In-situ observations have a double use: to fit the regression model and to calculate residuals. This could create a conflict between suitable locations for the detection of residuals and the efficient representation of feature space. A dual optimisation may be needed. The method requires prior knowledge about the spatiotemporal trend of the dynamic phenomenon and about the residual variogram. If information about the residual variogram is not available, mobile sensors could collect information in an initial sampling phase.

6.3. REFLECTIONS

This section contains general reflections on the societal relevance of the results, the methods and design choices used to carry out the research, and the integration of the two research challenges addressed in this thesis: sampling and mobility constraints. The use of sensor networks in environmental and geo-information sciences is also considered and future research is suggested. In these reflections, a literary analogy may be drawn with the robotic laws of the science fiction author Isaac Asimov (Asimov, 1942):

1. *A robot may not injure a human being or, through inaction, allow a human being to come to harm.*
2. *A robot must obey the orders given to it by human beings, except where such orders would conflict with the First Law.*
3. *A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws.*

6.3.1. Societal relevance

The recent environmental emergencies caused by the radioactive leaks at the Fukushima nuclear power plant in Japan in 2011 (Masson *et al.*, 2011), the eruption of the Eyjafjallajoekull volcano in Iceland in 2010 (Flentje *et al.*, 2010) and the oil spill in the Gulf of Mexico in 2010 (GEO, 2010) remind us that human beings and natural resources are vulnerable. Proper decisions based on real-time information gathered from environmental monitoring are critical for saving human lives and protecting natural resources from contamination and exhaustion.

This thesis contributes to meeting this challenge by developing strategies for autonomous sampling of the environment in real time and with high spatiotemporal resolutions. Specifically, it proposes spatial and spatiotemporal sampling strategies for use with mobile sensor networks in environmental monitoring (Chapters 4 and 5). The developed sampling strategies select informative sampling locations to improve the quality of decisions to be made using the sensor observations. Such decisions may be critical decisions in emergency situations, such as whether to evacuate inhabitants from a study area following a radioactive release, or whether to remove from the market food that might be contaminated by a chemical smoke plume. The strategies proved to be suitable for sampling phenomena with relative slow dynamics, which are usual in natural resources, such soil pollution, as well as phenomena with high dynamics, such as radioactive plumes and oil spills.

Additionally, this thesis considers mobility constraints with a view to appropriately managing sensor mobility within sampling strategies and accounting for different contexts (Chapters 2, 3 and 4). For instance, when monitoring highly dynamic phenomena such as radioactive releases, the most informative locations should be observed as soon as possible. The sensors to be moved to those locations can be selected by analysing mobility constraints such as distance to move, sensor speed, terrain slope and geographical barriers to identify the fastest sensor trajectory. Conversely, when monitoring slow phenomena, such as soil pollution monitoring, a relevant consideration is maximising the lifetime of the sensor network. In this case, the sensor to be moved can be selected by analysing mobility constraints to identify cost-reduced trajectories.

A literary analogy could be made with Asimov´s first law in the sense that mobile sensors must act to prevent harm to human beings and natural resources.

6.3.2. Methods and design choices

This thesis explored various methods and made design choices to support decisions on where sensors should be moved to improve phenomenon monitoring and how mobile sensors should behave under mobility constraints. This section motivates the chosen methods and summaries the design choices, and puts forward some starting points that could be useful for relaxing these design choices in future research.

Regarding mobility constraints, expert systems were explored for their potential to facilitate the integration of two sources of information needed to appropriately manage sensor mobility: real-time metadata about the current sensor network status and expert knowledge about how mobile sensors should behave. Three types of expert systems were examined: rule-based systems (Friedman-Hill, 2003), Bayesian networks (Charniak, 1991; Jensen and Nielsen, 2007; Pearl and Russell, 2001) and influence diagrams (Howard and Matheson, 2005; Jensen and Nielsen, 2007; Kjaerulff and Madsen, 2007). Rule-based systems handle deterministic if-then rules to describe the contexts of mobile sensor networks (Chapter 2). Bayesian networks provide a graph representation of mobility constraints, as well as probabilities propagation and inference of mobile sensor behaviour (Chapter 3). Influence diagrams link mobility constraints with decision theory, enabling decisions to be made, for instance, about the most suitable sensor to move under certain mobility constraints (Chapter 4). Surveyors and environmental scientists can encode their preferences by designing contextual rules (Chapter 2 and 3) and assigning cost values (Chapter 4).

Regarding sampling with mobile sensors, geostatistical methods, such as indicator kriging and regression kriging (Brus and Heuvelink, 2007; Hengl, 2009; Lin *et al.*, 2011), were used to identify the best locations to which sensors should be moved. As not every location in a study area can be observed, geostatistics and, in particular, kriging can help to predict phenomenon characteristics at unobserved locations (Chapter 4). Regression kriging is an option when correlated data are available, such as data from a physical dispersion model (Chapter 5). In addition, geostatistical methods have been combined with a decision theory measure: the expected value of information (Bhattacharjya *et al.*, 2010; de Bruin *et al.*, 2001; Kangas, 2010). This enables sampling locations to be selected according to their relevance for improving the quality of decisions that will be made using the sensor observations. Surveyors and environmental scientists can encode their preferences, for instance by assigning higher cost values to false negative than to false positive prediction errors.

The design choices are summarised below, including some starting points that could be useful for relaxing them in future research:

- Binary decisions were carried out to determine the presence or absence of a phenomenon or whether a sensor should move or not. However, the developed methods could also be used to make decisions concerning multiples states, and even several concatenated decisions.
- Sensor location was assumed to be known from GPS devices. However, other sensor location methods could be explored if GPS is not available and for indoor applications (Sahoo and Hwang, 2011; Yick *et al.*, 2008).
- A single sensor movement was performed at a time. However, the developed methods could be extended to support multiple movements, which could further improve the monitoring at each time step (Heuvelink *et al.*, 2010; Krause *et al.*, 2009).
- A single location was observed per sensor movement. However, a sequential optimisation could be done to also select informative

intermediate locations and gain more information with each sensor movement (Singh *et al.*, 2007).

- Sensors were moved along straight trajectories. However, cost-reduced trajectories could be selected based on cost surfaces calculated from mobility constraints.
- A centralised approach was used. However, a decentralised approach would be more efficient in terms of energy conservation and connectivity (Coles *et al.*, 2009; Duckham and Reitsma, 2009).
- Mobility constraints concerned mainly energy depletion and properties of the geographical space. However, for operational use, mobility constraints related to connectivity and data transmission also have to be considered.

A literary analogy could be made with Asimov´s second law in the sense that mobile sensors must obey 'orders' concerning where and how to move to improve phenomenon monitoring. These 'orders' are based on different methods and design choices. They are valid if they prevent human beings and natural resources coming to harm.

6.3.3. Integration of sampling strategies and mobility constraints; should mobility constraints also constrain the sampling strategies?

This thesis identifies and addresses two main research challenges concerning sampling strategies and mobility constraints within the scope of environmental monitoring. They have mainly been addressed separately. When considering the integration of sampling strategies and mobility constraints, the following question arises: Should mobility constraints also constrain the sampling strategy? In other words, should mobility constraints limit where sensors move in order to minimise resource consumption and the overall sensor network degradation?

Hitherto, mobile sensor network research has been primarily carried out within the computer sciences and has thus focused on using sensor mobility to reduce the main WSN limitations, such as network topology, connectivity and energy use (Wang *et al.*, 2010; Younis and Akkaya, 2008). Mobility constraints were primarily taken into account to protect and prolong the existence of the sensor network. For instance, Krause et al. (2009) placed and scheduled sensors by making use of a power-sensing quality trade-off to reduce energy consumption, and Zou and Chakrabarty (2007) used a trade-off criterion accounting for positive effects of mobility on tracking quality and negative effects on coverage, connectivity and energy conservation. In these approaches, mobility constraints limit where sensors are placed, which in turn also limits what sensors observe. Moreover, they usually lead to sensor self-protection rather than to the protection of human beings and natural resources.

In environmental monitoring, however, a prime purpose of mobile sensors is to improve monitoring to protect human beings and natural resources. Sensors are moved to essential locations, even though this may produce negative effects on coverage, connectivity or energy conservation. Thus, mobility constraints are useful for reducing such negative effects, but without constraining the sampling strategy. A literary analogy with Asimov´s second and third laws is useful to illustrate this situation. Consider a mobile sensor that receives an 'order' to move to an essential but risky location, in the sense that it could break network connectivity or even damage the sensor. In the computer science perspective, the mobile sensor would reject such an 'order' in the interests of protecting the sensor network and its own existence. However, in the environmental monitoring perspective, the mobile sensors must move to the essential location, and if necessary connectivity can be improved by relocating other sensors, while any damage to the sensor can be repaired or the sensor replaced. In other words, mobile sensors for environmental monitoring must protect their own existence as long as human beings and natural resources come to no harm.

6.3.4. Sensor networks in environmental and geo-information sciences

Over more than a decade of sensor network development, research was performed almost exclusively in the computer science arena. Research focused on the development of self-adaptive software, miniaturised hardware and decentralised configurations (Akyildiz *et al.*, 2002; Nittel, 2009; Yick *et al.*, 2008). The downside is that little attention was paid to the environmental phenomenon of interest (Zerger *et al.*, 2010). This reveals that research on sensor networks in computer science was not properly accompanied by research in the environmental and geo-information sciences. As a result, sensor networks are now a mature technology, but they are not yet widely used by surveyors and environmental scientists. This thesis represents an effort to bring together knowledge developed in the computer sciences and in the environmental and geo-information sciences, backed by realistic examples of the use of sensor networks in environmental applications, such as monitoring fire risk (Chapter 3) and monitoring a polluted smoke plume released when a chemical factory burned (Chapter 5).

I expect that sensor networks will become as widely used among surveyors and environmental scientists as an observation technique as remote sensing is today. However, further action will be needed to stimulate the operational use of sensor networks. First, a cost-benefit analysis should be carried out to compare sensor networks with traditional on the ground surveys and remote sensing techniques. This could reveal important advantages (and disadvantages) of sensor networks. Second, monitoring with sensor networks should be included in the curricula of environmental and geo-information studies. This would help future surveyors and environmentalist to gain familiarity with sensor networks concepts and their operational use.

This thesis examines a specific type of mobile sensor network: wireless sensor networks. However, other types of informal sensor networks could be also relevant for environmental monitoring, such as smart phones, volunteer citizens (i.e. volunteer geo-information) and sensor web (i.e. web-enablement sensor interoperability) (Bröring *et al.*, 2011; Craglia *et al.*, 2008). They bring to the geo-information science arena new and interesting challenges, such as sampling strategies using a vast variety of heterogeneous sensors of different quality or with non-controlled sensor mobility.

6.3.5. Future research

The following recommendations are given for further research:

- Extend the sampling strategy to dynamic phenomena to account for mobility constraints. Although the current strategy has been shown to provide sound locations to reduce misclassification costs, the management of sensor mobility is not yet satisfactory. Some sensors moved long distances to be located close to other mobile sensors. This consumed a considerable amount of battery power while observation was delayed. Therefore, mobility constraints could be useful for optimising other mobility aspects, for example by selecting suitable sensors to be moved once the sampling locations have been selected.
- Develop sampling strategies for use with mobile, constrained sensors in a decentralised approach. In this thesis, the developed mobility constraints model and sampling strategies took a centralised approach by gathering sensor observations from different sensors and mobility constraints from different contexts. This has two disadvantages: first, more sensor energy is consumed to centralise data and metadata; second, sensors may become isolated without being able to transmit data in real time (Coles *et al.*, 2009; Duckham and Reitsma, 2009). Therefore, a decentralised approach should be explored under the premise of using as much local information as possible, but still being able to depict the global picture.
- Focus on mobility constraints related to connectivity and data transmission. Although this thesis analysed several mobility constraints related to the properties of sensors, the geographical space and the

monitored phenomenon, it did not address those related to connectivity and data transition. This is relevant for operational implementations in which loss of connectivity will prevent data being delivered in real time.

- Elicit expert knowledge to reveal how experts expect mobile sensors to behave under mobility constraints. This thesis provides general approaches to account for mobility constraints; however, further research is needed to identify preferences for sensor mobility management in different types of environmental applications.
- Validate the proposed strategies in an operational implementation. Although the application results using a synthetic dataset were successful, the proposed strategies need to be operationally tested before using them in real-life situations.

References

Akyildiz, I., Su, W., Sankarasubramaniam, Y., Cayirci, E., 2002. Wireless sensor networks: a survey. Computer networks 38, 393-422.

Antoine-Santoni, T., Santucci, J., de Gentili, E., Silvani, X., Morandini, F., 2009. Performance of a Protected Wireless Sensor Network in a Fire. Analysis of Fire Spread and Data Transmission. Sensors 9, 5878.

Argany, M., Mostafavi, M., Karimipour, F., Gagné, C., 2011. A GIS Based Wireless Sensor Network Coverage Estimation and Optimization: A Voronoi Approach. Transactions on Computational Science XIV, 151-172.

Asimov, I., 1942. Runaround. Astounding Science Fiction 29, 94-103.

Baca, M., 2008. Introduction to Metadata: Revised Edition, 2nd edn Getty Research Institute.

Balazinska, M., Deshpande, A., Franklin, M.J., Gibbons, P.B., Gray, J., Hansen, M., Liebhold, M., Nath, S., Szalay, A., Tao, V., 2007. Data management in the worldwide sensor web. Pervasive Computing, IEEE 6, 30-40.

Baldauf, M., Dustdar, S., Rosenberg, F., 2007. A survey on context-aware systems. International Journal of Ad Hoc and Ubiquitous Computing 2, 263-277.

Ballari, D., de Bruin, S., Bregt, A.K., under review. Expected value of information for sampling dynamic phenomena with mobile sensors. International Journal of Applied Earth Observation and Geoinformation.

Ballari, D., de Bruin, S., Bregt, A.K., under review. Value of information and mobility constraints for sampling with mobile sensors. Computers & Geosciences.

Ballari, D., Wachowicz, M., Bregt, A.K., Manso-Callejo, M., 2012. A mobility constraint model to infer sensor behaviour in forest fire risk monitoring. Computers, Environment and Urban Systems 36, 81-95.

Ballari, D., Wachowicz, M., Manso-Callejo, M., 2009. Metadata behind the interoperability of Wireless Sensor Network. Sensors 9, 3635-3651.

Basagni, S., Carosi, A., Melachrinoudis, E., Petrioli, C., Wang, Z., 2008. Controlled sink mobility for prolonging wireless sensor networks lifetime. Wireless Networks 14, 831-858.

Benerecetti, M., Bouquet, P., Ghidini, C., 2000. Contextual reasoning distilled. Journal of Experimental & Theoretical Artificial Intelligence 12, 279-305.

Berger, J.O., 1985. Statistical decision theory and Bayesian analysis. Springer Series in Statistics, New York: Springer.

Bhattacharjya, D., Eidsvik, J., Mukerji, T., 2010. The Value of Information in Spatial Decision Making. Mathematical Geosciences 42, 141-163.

Bielza, C., Gómez, M., Shenoy, P.P., 2010. Modeling challenges with influence diagrams: Constructing probability and utility models. Decision Support Systems 49, 354-364.

Binder, J., Koller, D., Russell, S., Kanazawa, K., 1997. Adaptive probabilistic networks with hidden variables. Machine Learning 29, 213-244.

Bouquet, P., Ghidini, C., Giunchiglia, F., Blanzieri, E., 2003. Theories and uses of context in knowledge representation and reasoning. Journal of Pragmatics 35, 455-484.

Bouquet, P., Giunchiglia, F., Van Harmelen, F., Serafini, L., Stuckenschmidt, H., 2004. Contextualizing ontologies. Web Semantics: Science, Services and Agents on the World Wide Web 1, 325-343.

Brenning, A., Dubois, G., 2008. Towards generic real-time mapping algorithms for environmental monitoring and emergency detection. Stochastic Environmental Research and Risk Assessment 22, 601-611.

Bröring, A., Echterhoff, J., Jirka, S., Simonis, I., Everding, T., Stasch, C., Liang, S., Lemmens, R., 2011. New Generation Sensor Web Enablement. Sensors 11, 2652-2699.

Brus, D.J., Heuvelink, G., 2007. Optimization of sample patterns for universal kriging of environmental variables. Geoderma 138, 86-95.

Butler, Z., Rus, D., 2003. Event-based motion control for mobile-sensor networks. Pervasive Computing, IEEE 2, 34-42.

Campbell, A.T., Eisenman, S.B., Lane, N.D., Miluzzo, E., Peterson, R.A., Lu, H., Zheng, X., Musolesi, M., Fodor, K., Ahn, G.S., 2008. The rise of people-centric sensing. Internet Computing, IEEE 12, 12-21.

Coles, M.D., Azzi, D., Haynes, B.P., Hewitt, A., 2009. A Bayesian network approach to a biologically inspired motion strategy for mobile wireless sensor networks. Ad Hoc Networks 7, 1217-1228.

Craglia, M., Goodchild, M.F., Annoni, A., Camara, G., Gould, M., Kuhn, W., Mark, D., Masser, I., Maguire, D., Liang, S., Parsons, E., 2008. Next-Generation Digital Earth. A position paper from the Vespucci Initiative for the Advancement of Geographic Information Science. International Journal of Spatial Data Infrastructures Research 3, 146-167.

Charniak, E., 1991. Bayesian Networks without Tears. AI magazine 12, 50-63.

Chino, M., Nakayama, H., Nagai, H., Terada, H., Katata, G., Yamazawa, H., 2011. Preliminary Estimation of Release Amounts of 131 I and 137 Cs Accidentally Discharged from the Fukushima Daiichi Nuclear Power Plant into the Atmosphere. Journal of Nuclear Science and Technology 48, 1129-1134.

Chuvieco, E., Aguado, I., Yebra, M., Nieto, H., Salas, J., Martín, M., Vilar, L., Martínez, J., Martín, S., Ibarra, P., 2010. Development of a framework for fire risk assessment using remote sensing and geographic information system technologies. Ecological Modelling 221, 46-58.

Dantu, K., Rahimi, M., Shah, H., Babel, S., Dhariwal, A., Sukhatme, G.S., 2005. Robomote: enabling mobility in sensor networks. Proceedings of the 4th international symposium on Information processing in sensor networks. IEEE Press, Los Angeles, California, USA, pp. 404-409.

de Bruin, S., Bregt, A., van de Ven, M., 2001. Assessing fitness for use: the expected value of spatial data sets. International Journal of Geographical Information Science 15, 457-471.

de Bruin, S., Hunter, G.J., 2003. Making the trade-off between decision quality and information cost. PE & RS- Photogrammetric Engineering & Remote Sensing 69, 91-98.

de Gruijter, J., Brus, D.J., Bierkens, M.F.P., Knotters, M., 2006. Sampling for natural resource monitoring, 1st ed edn, Berlin Heidelberg New York: Springer, 332 pp.

De Roure, D., Jennings, N.R., Shadbolt, N.R., 2005. The semantic grid: Past, present, and future, Proceedings of the IEEE. IEEE, pp. 669-681.

Dempster, A., Laird, N., Rubin, D., 1977. Maximum likelihood from incomplete data via the EM algorithm. Journal of the Royal Statistical Society 39, 1-38.

Di Marzo Serugendo, G., Fitzgerald, J.S., Romanovsky, A., Guelfi, N., 2007. A generic framework for the engineering of self-adaptive and self-organising systems. Technical report series University of Newcastle upon Tyne. Available at: http://www.dcs.bbk.ac.uk/~dimarzo/papers/CS-TR-1018.pdf. (Accessed: 3 February 2012).

Dini, P., 2004. Internet, GRID, self-adaptability and beyond: are we ready? Proceedings of the 15th International Workshop on Database and Expert Systems Applications, Zaragoza, Spain, pp. 782-788.

Dlamini, W., 2010. A Bayesian belief network analysis of factors influencing wildfire occurrence in Swaziland. Environmental Modelling & Software 25, 199-208.

Donaldson-Matasci, M.C., Bergstrom, C.T., Lachmann, M., 2010. The fitness value of information. Oikos 119, 219-230.

Doolin, D., Sitar, N., 2005. Wireless sensors for wildfire monitoring. Proceedings of the SPIE Symposium on Smart Structures & Materials, San Diego, pp. 477-484.

Dubois, G., Cornford, D., Hristopulos, D., Pebesma, E., Pilz, J., 2011. Introduction to this special issue on geoinformatics for environmental surveillance. Computers & Geosciences 37, 277-279.

Duckham, M., Reitsma, F., 2009. Decentralized environmental simulation and feedback in robust geosensor networks. Computers, Environment and Urban Systems 33, 256-268.

Eisenman, S., Miluzzo, E., Lane, N., Peterson, R., Ahn, G., Campbell, A., 2007. The BikeNet mobile sensing system for cyclist experience mapping. Proceedings of the 5th Conference On Embedded Networked Sensor Systems, pp. 87-101.

Ekici, E., Gu, Y., Bozdag, D., 2006. Mobility-based communication in wireless sensor networks. Communications Magazine, IEEE 44, 56-62.

Eriksson, H., 2003. Using jesstab to integrate protégé and jess. Intelligent Systems, IEEE 18, 43-50.

Erman, A., Hoesel, L., Havinga, P., Wu, J., 2009. Enabling mobility in heterogeneous wireless sensor networks cooperating with UAVs for mission-critical management. Wireless Communications, IEEE 15, 38-46.

Flentje, H., Claude, H., Elste, T., Gilge, S., Köhler, U., Plass-Dülmer, C., Steinbrecht, W., Thomas, W., Werner, A., Fricke, W., 2010. The Eyjafjallajoekull eruption in April 2010-detection of volcanic plume using in-situ measurements, ozone sondes and lidar-ceilometer profiles. Atmospheric Chemistry and Physics 10, 10085-10092.

Friedman-Hill, E., 2003. Jess in Action: Java Rule-Based Systems. Manning, 480 pp.

GEO, 2010. Crafting geoinformation. Group on Earth Observations. In: Williams, M., Achache, J. (Eds.). GEO Secretariat, Geneva, Switzerland.

Giunchiglia, F., 1993. Contextual reasoning. Epistemologia, special issue on I Linguaggi e le Macchine 16, 345-364.

Giunchiglia, F., Bouquet, P., 1997. Introduction to contextual reasoning. An Artificial Intelligence Perspective. Perspectives on Cognitive Science 3, 138-159.

Grace, P., Blair, G.S., Cortes, C.F., Bencomo, N., 2008. Engineering complex adaptations in highly heterogeneous distributed systems. Proceedings of the 2nd International Conference on Autonomic Computing and Communication Systems - AUTONOMICS 2008, Turin, Italy, pp. 23-25.

GSDI, 2009. The Spatial Data Infrastructure Cookbook. Available at: http://www.gsdi.org/gsdicookbookindex. (Accessed: 3 February 2012).

Gungor, V.C., Hancke, G.P., 2009. Industrial wireless sensor networks: Challenges, design principles, and technical approaches. Transactions on industrial Electronics, IEEE 56, 4258-4265.

Hartung, C., Han, R., Seielstad, C., Holbrook, S., 2006. FireWxNet: a multi-tiered portable wireless system for monitoring weather conditions in wildland fire environments. Proceedings of the International Conference on Mobile systems, Applications and Services - MobiSys'06. ACM, Uppsala, Sweden, pp. 28-41.

He, T., Krishnamurthy, S., Luo, L., Yan, T., Gu, L., Stoleru, R., Zhou, G., Cao, Q., Vicaire, P., Stankovic, J.A., others, 2006. VigilNet: An integrated sensor network system for energy-efficient surveillance. ACM Transactions on Sensor Networks, TOSN, 2, 1-38.

Heckerman, D., 2008. A tutorial on learning with Bayesian networks, In: Holmes, D.E., Jain, L.C. (Eds.). Innovations in Bayesian Networks. Studies in Computational Intelligence. Springer, Berlin, pp. 33-82.

Hefeeda, M., Bagheri, M., 2008. Forest fire modeling and early detection using wireless sensor networks. Ad Hoc & Sensor Wireless Networks 7, 169-224.

Heinzelman, W., Kulik, J., Balakrishnan, H., 1999. Adaptive protocols for information dissemination in wireless sensor networks. Proceedings of the 5th Annual ACM/IEEE International Conference on Mobile Computing and Networking, Seattle, Washington, USA, pp. 174-185.

Hengl, T., 2009. A Practical Guide to Geostatistical Mapping, 2nd ed. University of Amsterdam, Amsterdam, p. 291.

Heuvelink, G., Griffith, D.A., 2010. Space-Time Geostatistics for Geography: A Case Study of Radiation Monitoring Across Parts of Germany. Geographical Analysis 42, 161-179.

Heuvelink, G., Jiang, Z., De Bruin, S., Twenhöfel, C., 2010. Optimization of mobile radioactivity monitoring networks. International Journal of Geographical Information Science 24, 365-382.

Højsgaard, S., 2009. gRain; A Graphical Independence Networks package in R. Available at: http://cran.r-project.org/web/packages/gRain/index.html. (Accessed: 3 February 2012).

Horsburgh, J.S., Spackman Jones, A., Stevens, D.K., Tarboton, D.G., Mesner, N.O., 2010. A sensor network for high frequency estimation of water quality constituent fluxes using surrogates. Environmental Modelling & Software 25, 1031-1044.

Hosmer, D.W., Lemeshow, S., 2000. Applied logistic regression. Second edn Wiley-Interscience.

Hossain, A., Biswas, P., Chakrabarti, S., 2008. Sensing Models and Its Impact on Network Coverage in Wireless Sensor Network. Proceedings of the IEEE Region 10 and the 3rd International Conference on Industrial and Information Systems, Kharagpur, pp. 1-5.

Howard, A., Mataric, M.J., Sukhatme, G.S., 2002. Mobile sensor network deployment using potential fields: A distributed, scalable solution to the area coverage problem. Proceedings of the 6th International Symposium on Distributed Autonomous Robotics Systems, DARS02, pp. 299-308.

Howard, R.A., Matheson, J.E., 2005. Influence diagrams. Decision Analysis 2, 127-143.

Huang, C., Darwiche, A., 1996. Inference in belief networks: A procedural guide. International Journal of Approximate Reasoning 15, 225-263.

Huang, C., Tseng, Y., 2005. The coverage problem in a wireless sensor network. Mobile Networks and Applications 10, 519-528.

Hull, B., Bychkovsky, V., Zhang, Y., Chen, K., Goraczko, M., Miu, A., Shih, E., Balakrishnan, H., Madden, S., 2006. CarTel: a distributed mobile sensor computing system. Proceedings of the 4th international conference on Embedded networked sensor systems, SenSys '06, p. 138.

Indulska, J., Henricksen, K., Hu, P., 2006. Towards a standards-based autonomic context management system. Autonomic and Trusted Computing. Lecture Notes in Computer Science 4158, 26-37.

Intanagonwiwat, C., Govindan, R., Estrin, D., Heidemann, J., Silva, F., 2003. Directed diffusion for wireless sensor networking. Networking, IEEE/ACM Transactions on 11, 2-16.

Jain, S., Shah, R., Brunette, W., Borriello, G., Roy, S., 2006. Exploiting mobility for energy efficient data collection in wireless sensor networks. Mobile Networks and Applications 11, 327-339.

Jensen, F., Nielsen, T., 2007. Bayesian networks and decision graphs. 2nd edn, Berlin: Springer.

Jiang, P., Xia, H., He, Z., Wang, Z., 2009. Design of a Water Environment Monitoring System Based on Wireless Sensor Networks. Sensors 9, 6411-6434.

Jordan, M., 1998. Learning in graphical models, Cambridge: MIT Press.

Juang, P., Oki, H., Wang, Y., Martonosi, M., Peh, L., Rubenstein, D., 2002. Energy-efficient computing for wildlife tracking: Design tradeoffs and early experiences with zebranet, SIGOPS Operating Systems Review. Proceedings of the 10th annual conference on Architectural Support for Programming Languages and Operating Systems, pp. 96-107.

Jun, J., Xie, B., Agrawal, D., 2009. Wireless Mobile Sensor Networks: Protocols and Mobility Strategies, In: Misra, S.C., Woungang, I., Misra, S., Jun, J.H., Xie, B., Agrawal, D.P. (Eds.), Guide to Wireless Sensor Networks. Springer London, pp. 611-638.

Kangas, A., 2010. Value of forest information. European Journal of Forest Research 129, 863-874.

Kho, J., Rogers, A., Jennings, N.R., 2009. Decentralized control of adaptive sampling in wireless sensor networks. ACM Transactions on Sensor Networks (TOSN) 5, 19.

Kjaerulff, U.B., Madsen, A.L., 2007. Bayesian networks and influence diagrams: a guide to construction and analysis. Springer.

Krause, A., Rajagopal, R., Gupta, A., Guestrin, C., 2009. Simultaneous placement and scheduling of sensors. Proceedings of the 2009 International Conference on Information Processing in Sensor Networks, pp. 181-192.

Krause, A., Singh, A., Guestrin, C., 2008. Near-optimal sensor placements in Gaussian processes: Theory, efficient algorithms and empirical studies. Journal of Machine Learning Research 9, 235-284.

Kyriakidis, P.C., Journel, A.G., 1999. Geostatistical space-time models: a review. Mathematical geology 31, 651-684.

Lawson, B., Armitage, O., 2008. Weather guide for the Canadian Forest Fire Danger Rating System Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre. Edmonton. Available at: http://fire.ak.blm.gov/content/weather/2008%20CFFDRS%20Weather%20Guide.pdf(Accessed: 3 February 2012).

Liang, S.H.L., Croitoru, A., Tao, C.V., 2005. A distributed geospatial infrastructure for Sensor Web. Computers & Geosciences 31, 221-231.

Lin, Y.P., Cheng, B.Y., Chu, H.J., Chang, T.K., Yu, H.L., 2011. Assessing how heavy metal pollution and human activity are related by using logistic regression and kriging methods. Geoderma 163, 275-282.

Liu, B., Brass, P., Dousse, O., Nain, P., Towsley, D., 2005. Mobility improves coverage of sensor networks. Proceedings of the 6th international symposium on Mobile ad hoc networking and computing, Urbana-Champaign, USA pp. 300-308.

Manning, C., 2007. Logistic regression (with R). Available at: http://nlp.stanford.edu/~manning/courses/ling289/logistic.pdf. (Accessed: 3 February 2012).

Manso, M.A., Wachowicz, M., Bernabé, M.A., 2009. Towards an integrated model of interoperability for spatial data infrastructures. Transactions in GIS 13, 43-67.

Masson, o., Baeza, A., Bieringer, J., Brudecki, K., Bucci, S., Cappai, M., Carvalho, F., Connan, O., Cosma, C., Dalheimer, A., 2011. Tracking of airborne radionuclides from the damaged Fukushima Dai-Ichi nuclear reactors by European Networks. Environmental science & technology 45, 7670-7677.

Melles, S.J., Heuvelink, G.B.M., Twenhöfel, C.J.W., van Dijk, A., Hiemstra, P.H., Baume, O., Stöhlker, U., 2011. Optimizing the spatial pattern of networks for monitoring radioactive releases. Computers & Geosciences 37, 280-288.

MEMSIC, 2010. Wireless Sensor Networks. Available at: http://www.memsic.com/. (Accessed: 3 February 2012).

Milton, R., Steed, A., 2007. Mapping carbon monoxide using GPS tracked sensors. Environmental monitoring and Assessment 124, 1-19.

Minasny, B., McBratney, A.B., 2006. A conditioned Latin hypercube method for sampling in the presence of ancillary information. Computers & Geosciences 32, 1378-1388.

Minasny, B., McBratney, A.B., Walvoort, D.J.J., 2007. The variance quadtree algorithm: Use for spatial sampling design. Computers & Geosciences 33, 383-392.

Myers, D.E., 2004. Estimating and Modeling Space-time variograms. Proceedings of the TIES Spatial Accuracy, Portland Maine.

Needham, C.J., Bradford, J.R., Bulpitt, A.J., Westhead, D.R., 2007. A Primer on Learning in Bayesian Networks for Computational Biology. PLoS Computational Biology 3, e129.

Netica, 2009. Norsys Software Corporation. Available at: http://www.norsys.com/. (Accessed: 3 February 2012).

Nittel, S., 2009. A survey of geosensor networks: advances in dynamic environmental monitoring. Sensors 9, 5664-5678.

Nittel, S., Stefanidis, A., 2004. GeoSensor Networks and Virtual GeoReality, 1st edn. GeoSensors Networks. CRC Press: Boca Raton.

Obashi, Y., Kokogawa, T., Zheng, Y., Chen, H., Mineno, H., Mizuno, T., 2007. Evaluation of Metadata-Based Data Aggregation Scheme in Clustering Wireless Sensor Networks, Knowledge-Based Intelligent Information and Engineering Systems. Springer, pp. 477-483.

Pearl, J., Russell, S., 2001. Bayesian networks, In: Arbib, M. (Ed.), Handbook of brain theory and neural networks. MIT Press, Cambridge, pp. 157-160.

Pebesma, E.J., Bivand, R.S., 2005. Classes and methods for spatial data in R. R News 5, 9-13.

Pebesma, E.J., Wesseling, C.G., 1998. Gstat: a program for geostatistical modelling, prediction and simulation. Computers & Geosciences 24, 17-31.

Pollino, C.A., Woodberry, O., Nicholson, A., Korb, K., Hart, B.T., 2007. Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment. Environmental Modelling & Software 22, 1140-1152.

Porter, J., Nagy, E., Kratz, T., Hanson, P., Collins, S., Arzberger, P., 2009. New eyes on the world: Advanced sensors for ecology. BioScience 59, 385-397.

PostGIS, 2007. Spatial extension for PostgreSQL. Available at: http://postgis.refractions.net/. (Accessed: 3 February 2012).

R Development Core Team, 2010. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0. Available at: http://www.R-project.org.

Rodriguez-Lado, L., Hengl, T., Reuter, H.I., 2008. Heavy metals in European soils: A geostatistical analysis of the FOREGS Geochemical database. Geoderma 148, 189-199.

Romic, M., Hengl, T., Romic, D., Husnjak, S., 2007. Representing soil pollution by heavy metals using continuous limitation scores. Computers & Geosciences 33, 1316-1326.

Ruiz, L., Nogueira, J., Laureiro, A., 2004. Sensor network management, In: Ilyas, M., Mahgoub, I. (Eds.), Handbook of Sensor Networks: Compact Wireless and Wired Sensing Systems, 1st ed. CRC Press: Boca Raton.

Rundel, P.W., Graham, E.A., Allen, M.F., Fisher, J.C., Harmon, T.C., 2009. Environmental sensor networks in ecological research. New Phytologist 182, 589-607.

Sahin, Y., 2007. Animals as mobile biological sensors for forest fire detection. Sensors 7, 3084-3099.

Sahoo, P.K., Hwang, I., 2011. Collaborative Localization Algorithms for Wireless Sensor Networks with Reduced Localization Error. Sensors 11, 9989-10009.

Sarkar, D., 2008. Lattice: Multivariate Data Visualization with R, Springer, New York.

Sheth, A., Henson, C., Sahoo, S., 2008. Semantic sensor web. Internet Computing, IEEE 12, 78-83.

Singh, A., Budzik, D., Chen, W., Batalin, M., Kaiser, W., 2006. Multiscale Sensing: A new paradigm for actuated sensing of high frequency dynamic phenomena. Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems, Beijing, pp. 328-335.

Singh, A., Krause, A., Guestrin, C., Kaiser, W., Batalin, M., 2007. Efficient planning of informative paths for multiple robots, International Joint Conferences on Artificial Intelligence, Hyderabad, India.

Son, B., Her, Y., Kim, J., 2006. A design and implementation of forest-fires surveillance system based on wireless sensor networks for South Korea mountains. International Journal of Computer Science and Network Security, IJCSNS 6, 124-130.

Sutton, O.G., 1932. A Theory of Eddy Diffusion in the Atmosphere. Proceedings of the Royal Society A Mathematical Physical and Engineering Sciences 135, 143-165.

Terzis, A., Musaloiu-E, R., Cogan, J., Szlavecz, K., Szalay, A., Gray, J., Ozer, S., Liang, C., Gupchup, J., Burns, R., 2010. Wireless sensor networks for soil science. International Journal of Sensor Networks 7, 53-70.

Tillé, Y., Matei, A., 2011. Sampling package for R. Available at: http://cran.r-project.org/package=sampling. (Accessed: 3 February 2012).

Van Wagner, C., Pickett, T., 1985. Equations and FORTRAN program for the Canadian Forest Fire Weather Index System Canadian Forestry Service. Available at: http://cfs.nrcan.gc.ca/pubwarehouse/pdfs/19973.pdf. (Accessed: 3 February 2012).

van Zyl, T.L., Simonis, I., Mcferren, G., 2009. The sensor web: systems of sensor systems. International Journal of Digital Earth 2, 16-30.

Varis, O., 1997. Bayesian decision analysis for environmental and resource management. Environmental Modelling & Software 12, 177-185.

Verma, A., Sawant, H., Tan, J., 2006. Selection and navigation of mobile sensor nodes using a sensor network. Pervasive and Mobile Computing 2, 65-84.

W3C, 2009. W3C Semantic Sensor Network Incubator Group. Available at: http://www.w3.org/2005/Incubator/ssn/. (Accessed: 3 February 2012).

Walkowski, A.C., 2008. Model Based Optimization of Mobile Geosensor Networks, In: Bernard, L., Friis-Christensen, A., Pundt, H. (Eds.), The European Information Society. Springer Berlin Heidelberg, pp. 51-66.

Walvoort, D., Brus, D., de Gruijter, J., 2010. An R package for spatial coverage sampling and random sampling from compact geographical strata by k-means. Computers & Geosciences 36, 1261-1267.

Wang, B., Lim, H., Ma, D., 2009. A survey of movement strategies for improving network coverage in wireless sensor networks. Computer Communications 32, 1427-1436.

Wang, Y.C., Peng, W.C., Tseng, Y.C., 2010. Energy-Balanced Dispatch of Mobile Sensors in a Hybrid Wireless Sensor Network. Transactions on Parallel and Distributed Systems, IEEE 21, 1836-1850.

Wang, Y.C., Wu, F.J., Tseng, Y.C., 2012. Mobility management algorithms and applications for mobile sensor networks. Wireless Communications and Mobile Computing 12, 7-21.

Wark, T., Corke, P., Sikka, P., Klingbeil, L., Guo, Y., Crossman, C., Valencia, P., Swain, D., Bishop-Hurley, G., 2007. Transforming agriculture through pervasive wireless sensor networks. Pervasive Computing, IEEE 6, 50-57.

Werner-Allen, G., Lorincz, K., Ruiz, M., Marcillo, O., Johnson, J., Lees, J., Welsh, M., 2006. Deploying a wireless sensor network on an active volcano. Internet Computing, IEEE 10, 18-25.

Wiegerinck, W., Kappen, B., Burgers, W., 2010. Bayesian Networks for Expert Systems: Theory and Practical Applications, In: Babuška, R., Groen, F. (Eds.), Interactive Collaborative Information Systems. Springer Berlin, pp. 547-578.

Willett, R., Martin, A., Nowak, R., 2004. Backcasting: adaptive sampling for sensor networks. Proceedings of the Third International Symposium on Information Processing in Sensor Networks, IPSN. IEEE, pp. 124 -133

Wood, A., Stankovic, J., Virone, G., Selavo, L., He, Z., Cao, Q., Doan, T., Wu, Y., Fang, L., Stoleru, R., 2008. Context-aware wireless sensor networks for assisted living and residential monitoring. Network, IEEE 22, 26-33.

Woodberry, O., Nicholson, A., Korb, K., Pollino, C., 2005. Parameterising bayesian networks, In: Webb, G.I., Xinghuo, Y. (Ed.), AI 2004: Advances in Artificial Intelligence. Springer Berlin Heidelberg, pp. 711-745.

Xu, Y., Choi, J., 2011. Adaptive sampling for learning Gaussian processes using mobile sensor networks. Sensors 11, 3051-3066.

Yick, J., Mukherjee, B., Ghosal, D., 2008. Wireless sensor network survey. Computer networks 52, 2292-2330.

Younis, M., Akkaya, K., 2008. Strategies and techniques for node placement in wireless sensor networks: A survey. Ad Hoc Networks 6, 621-655.

Yu, L., Wang, N., Meng, X., 2005. Real-time forest fire detection with wireless sensor networks. Proceedings of the International Conference On Wireless Communications, Networking and Mobile Computing - WiMob'05, Montreal, Canada, pp. 1214-1217.

Zerger, A., Viscarra Rossel, R.A., Swain, D.L., Wark, T., Handcock, R.N., Doerr, V.A.J., Bishop-Hurley, G.J., Doerr, E.D., Gibbons, P.G., Lobsey, C., 2010. Environmental sensor networks for vegetation, animal and soil sciences. International Journal of Applied Earth Observation and Geoinformation 12, 303-316.

Zhang, C., Guan, H., Li, M., Wu, M.Y., Zhang, W., Tang, F., 2006. Model-aided metadata management for wireless sensor networks. Advances in Grid and Pervasive Computing. Lecture Notes in Computer Science 3947, 259-268.

Zou, Y., Chakrabarty, K., 2007. Distributed mobility management for target tracking in mobile sensor networks. Transactions on Mobile Computing, IEEE 6, 872-887.

Zoysa, K.D., Keppitiyagama, C., Seneviratne, G.P., Shihan, W.W., 2007. A public transport system based sensor network for road surface condition monitoring. Proceedings of the 2007 workshop on networked systems for developing regions, Kyoto, Japan, p. 9.

Summaries in English, Dutch and Spanish

SUMMARY

Vulnerability to natural disasters and the human pressure on natural resources have increased the need for environmental monitoring. Proper decisions, based on real-time information gathered from the environment, are critical to protecting human lives and natural resources. To this end, mobile sensor networks, such as wireless sensor networks, are promising sensing systems for flexible and autonomous gathering of such information. Mobile sensor networks consist of geographically deployed sensors very close to a phenomenon of interest. The sensors are autonomous, self-configured, small, lightweight and low powered, and they become mobile when they are attached to mobile objects such as robots, people or bikes.

Research on mobile sensor networks has focused primarily on using sensor mobility to reduce the main sensor network limitations in terms of network topology, connectivity and energy conservation. However, how sensor mobility could improve environmental monitoring still remains largely unexplored. Addressing this requires the consideration of two main mobility aspects: sampling and mobility constraints. Sampling is about where mobile sensors should be moved, while mobility constraints are about how such movements should be handled, considering the context in which the monitoring is carried out. This thesis explores approaches for sensor mobility within a wireless sensor network for use in environmental monitoring. To achieve this goal, four sub-objectives were defined:

1. Explore the use of metadata to describe the dynamic status of sensor networks.
2. Develop a mobility constraint model to infer mobile sensor behaviour.
3. Develop a method to adapt spatial sampling using mobile, constrained sensors.
4. Extend the developed adaptive sampling method to monitoring highly dynamic environmental phenomena.

Chapter 2 explores the use of metadata to describe the dynamic status of sensor networks. A context model was proposed to describe the general situation in which a sensor network is monitoring. The model consists of four types of contexts: sensor, network, sensing and organisation, where each of the contexts describes the sensor network from a different perspective. Metadata, which are descriptors of observed data, sensor configurations and functionalities, are used as parameters to describe what is happening in the

different contexts. The results reveal that metadata are suitable for describing sensor network status within different contexts and reporting the status back to other components, systems or users.

Chapter 3 develops a model which describes mobility constraints for inferring mobile sensor behaviour. The proposed mobility constraint model consists of three components: first, the context typology proposed in Chapter 2 to describe mobility constraints within the different contexts; second, a context graph, modelled as a Bayesian network, to encode dependencies of mobility constraints within the same or different contexts, as well as among mobility constraints and sensor behaviour; and third, contextual rules to encode how dependent mobility constraints are expected to constrain sensor behaviour. Metadata values for the monitored phenomenon and sensor properties are used to feed the context graph. They are propagated through the graph structure, and the contextual rules are used to infer the most suitable behaviour. The model was used to simulate the behaviour of a mobile sensor network to obtain a suitable spatial coverage in low and high fire risk scenarios. It was shown that the mobility constraint model successfully inferred behaviour, such as sleeping sensors, moving sensors and deploying more sensors to enhance spatial coverage.

Chapter 4 develops a spatial sampling strategy for use with mobile, constrained sensors according to the expected value of information (EVoI) and mobility constraints. EVoI allows decisions to be made about the location to observe. It minimises the expected costs of wrong predictions about a phenomenon using a spatially aggregated EVoI criterion. Mobility constraints allow decisions to be made about which sensor to move. A cost-distance criterion is used to minimise unwanted effects of sensor mobility on the sensor network itself, such as energy depletion. The method was assessed by comparing it with a random selection of sample locations combined with sensor selection based on a minimum Euclidian distance criterion. The results demonstrate that EVoI enables selection of the most informative locations, while mobility constraints provide the needed context for sensor selection.

Chapter 5 extends the method developed in Chapter 4 for the case of highly dynamic phenomena. It develops a method for deciding when and where to sample a dynamic phenomenon using mobile sensors. The optimisation criterion is to maximise the EVoI from a new sensor deployment at each time step. The method was demonstrated in a scenario in which a simulated fire in a chemical factory released polluted smoke into the open air. The plume varied in space and time because of variations in atmospheric conditions and could be only partially predicted by a deterministic dispersion model. In-situ observations acquired by mobile sensors were considered to improve predictions. A comparison with random sensor movements and the previous sensor deployment without performing sensor movements shows that the optimised sensor mobility successfully reduced risk caused by poor model predictions.

Chapter 6 synthesises the main findings and presents my reflections on the implications of such findings. Mobile sensors for environmental monitoring are relevant to improving monitoring by selecting sampling locations that deliver the information that most improves the quality of decisions for protecting human lives and natural resources. Mobility constraints are relevant to managing sensor mobility within sampling strategies. The traditional consideration of mobility constraints within the field of computer sciences mainly leads to sensor self-protection rather than to the protection of human beings and natural resources. By contrast, when used for environmental monitoring, mobile sensors should above all improve monitoring performance, even thought this might produce negative effects on coverage, connectivity or energy consumption. Thus, mobility constraints are useful for reducing such negative effects without constraining the sampling strategy. Although sensor networks are now a mature technology, they are not yet widely used by surveyors and environmental scientists. The operational use of sensor networks in geo-information and environmental sciences therefore needs to be further stimulated. Although this thesis focuses on wireless sensor network, other types of informal sensor networks could be also relevant for environmental monitoring, such as smart phones, volunteer citizens and sensor web. Finally, the following recommendations are given for further research: extend the sampling strategy for dynamic phenomena to take account of mobility constraints; develop sampling strategies that take a decentralised approach; focus on mobility constraints related to connectivity and data transmission; elicit expert knowledge to reveal preferences for sensor mobility under mobility constraints within different types of environmental applications; and validate the proposed strategies in operational implementations.

SAMENVATTING

Natuurlijke hulpbronnen in wereld staan onder druk door het toegenomen gebruik hiervan door de mensheid. Om verstandig met deze hulpbronnen om te gaan is monitoring van de status en de ontwikkelingen in deze hulpbronnen belangrijk. Hiervoor worden in toenemende mate sensornetwerken ingezet. Een speciale vorm van sensornetwerken zijn de zogenaamde mobiele sensornetwerken. Deze mobiele sensornetwerken kunnen zeer flexibel en autonoom informatie verzamelen over het te monitoren verschijnsel. De sensoren binnen een mobiel sensornetwerk zijn vaak zelf configurerend, klein, lichtgewicht en energiezuinig. Ze worden mobiel door ze verbinden aan bijvoorbeeld robots of mensen.

Onderzoek op het vlak van mobiele sensor netwerken heeft zich tot nu toe vooral gericht op het opheffen van beperkingen op het vlak van netwerk topologie, verbondenheid en energie besparing. Onderzoek naar het gebruik van mobiele sensoren voor het monitoren van allerlei ruimtelijke verschijnselen heeft veel minder aandacht gekregen. Dit onderzoek richt zich vooral op dit laatste onderdeel, met speciale aandacht voor de aspecten bemonstering en mobiliteitsbeperking . Bemonstering richt zich op de locaties waar de mobiele sensor zich naartoe zou moeten bewegen, terwijl mobiliteitsbeperking zich richt op factoren die de beweging van de sensoren beperken. Deze thesis richt zich op het onderzoeken van methoden voor sensor mobiliteit binnen draadloze sensornetwerken voor monitoren van de omgeving. Om dit algemene doel te bereiken zijn de volgende doelen geformuleerd:

1. Verkennen van de mogelijkheden van metadata voor het beschrijven van de dynamische toestand van sensor netwerken;
2. Ontwikkeling van een model van mobiliteitsbeperking waarmee het gedrag van mobiele sensoren beschreven wordt;
3. Ontwikkeling van een methode voor ruimtelijke bemonstering door mobile sensoren onder mobiliteitsbeperkende omstandigheden;
4. Uitbreiding van de ontwikkelde bemonsteringsmethode naar het monitoren van sterk dynamische ruimtelijke verschijnselen.

In hoofdstuk 2 worden de mogelijkheden verkend voor het gebruik van metadata voor het beschrijven van dynamische toestand van sensor netwerken. Een contextmodel wordt voorgesteld om de toestand van een sensor netwerk te beschrijven. Daarbij zijn vier verschillende contexten te onderscheiden: sensor, netwerk, waarnemen en organisatie. Iedere context beschrijft een ander gezichtspunt op het sensor netwerk. Metadata worden gebruikt om de sensorconfiguratie en de functionaliteit binnen de verschillende contexten te beschrijven. De resultaten laten zien dat metadata erg geschikt zijn voor het

beschrijven van de status van het sensornetwerk en communicatie hierover naar andere componenten, systemen en gebruikers.

Hoofdstuk 3 behandelt de ontwikkeling van een model van mobiliteitsbeperking voor het beschrijven van het gedrag van mobiele sensoren. Het model bestaat uit drie componenten. De eerste component is de context topologie zoals beschreven in hoofdstuk 2. De tweede component is de “context graph”, gemodelleerd als Bayesiaans netwerk, voor het beschrijven van de afhankelijkheden tussen mobiliteitsbeperkende omstandigheden, de verschillende contexten en het gedrag van sensoren. De derde component zijn de “contextual rules”, die de relatie beschrijven tussen de mobiliteitsbeperkende omstandigheden en het gedrag van de sensoren. Het ontwikkelde mobiliteitsbeperkingsmodel is vervolgens toegepast in een gesimuleerde case studie, waarbij het doel was om adequate ruimtelijke sensor dekking te krijgen voor het monitoren van bosbrandgevaar. Zowel een laag als en hoog bosbrandgevaar scenario zijn gesimuleerd. Het bleek dat ontwikkelde model succesvol kon worden ingezet om gedrag van sensoren te sturen, zoals het “slapen” of bewegen van sensoren.

In hoofdstuk 4 wordt een ruimtelijke bemonsteringsmethode voorgesteld voor mobiele sensoren. De methode maakt gebruik van het concept “verwachte waarde van informatie” of “expected value of information (EVoI)”. Op basis van de EVoI is het mogelijk om een onderbouwd besluit te nemen over de meest geschikt locatie voor het doen van een sensor waarneming. De methode minimaliseert de verwachte kosten van een verkeerde voorspelling over een ruimtelijke verschijnsel. Gecombineerd met informatie over mobiliteitsbeperkende omstandigheden leidt dit tot een besluit over de meest geëigende sensor om zich naar de geselecteerde locatie te bewegen voor het uitvoeren van een waarneming. De ontwikkelde methode is vergeleken met een procedure waarbij de waar te nemen locaties aselect zijn gekozen in combinatie met selectie voor een te verplaatsen sensor op basis van een Euclidisch afstandscriterium. De ontwikkelde methode op basis van “de verwachte waarde van informatie” leverde meer informatie tegen lagere kosten.

In hoofdstuk 5 wordt de ontwikkelde methode (hoofdstuk 4) uitgebreid naar het waarnemen door mobiele sensoren van sterk dynamische ruimtelijke verschijnselen. In deze uitgebreide methode wordt het criterium “verwachte waarde van informatie” na iedere tijdstap geëvalueerd op basis van de waarnemingen en gemodelleerd dynamische gedrag van een ruimtelijk verschijnsel. De voorgestelde methode is toegepast in een gesimuleerde case studie waarbij brand in een chemische fabriek leidde tot het vrijkomen van een verontreinigende rookwolk. De rookwolk verplaatste zich in de ruimte gedurende een bepaalde periode, de beweging ervan werd beïnvloed door atmosferische omstandigheden. Het ruimtelijk-temporele gedrag van de rookwolk kon maar gedeeltelijk verklaard worden door een deterministisch dispersiemodel. De ontwikkelende methode is vervolgens gebruikt voor het verrichten van in-situ waarnemen door mobiele sensoren voor het verbeteren van de voorspellingen over de locatie van de rookwolk. De resultaten zijn vergeleken met een situatie waarbij de sensoren zich op een aselecte wijze verplaatsten en met een vast sensor netwerk. Het bleek dat de voorgestelde methode op basis van de EVoI betere voorspellingen van locatie van de rookwolk tot gevolg had.

Hoofdstuk 6 reflecteert op de resultaten van het onderzoek en gaat in op mogelijke implicaties. Mobiele sensoren stellen de mensheid in staat om van zeer uiteenlopende ruimtelijke verschijnselen informatie te verzamelen en deze informatie te gebruiken voor verstandige beslissingen over bijvoorbeeld het gebruik van onze natuurlijke hulpbronnen. Hoewel we op sensorvlak kunnen spreken van een volwassen technologie zien we dat het operationele gebruik van mobiele sensoren in bijvoorbeeld in de geo-informatie en de omgevingswetenschappen tot nu tot beperkt is. Voor een deel heeft dit te maken met het ontbreken van goede waarnemingsmethoden en het kunnen omgaan mobiliteitsbeperkende omstandigheden. Op beide terreinen zijn in dit onderzoek methoden ontwikkeld en geëvalueerd. Onderzoek naar mobibliteitsbeperkende omstandigheden heeft zich zowel gericht op beperkingen van de sensor als belemmeringen in de omgeving. Gecombineerde evaluatie hiervan is belangrijk voor effectief en efficiënt inzetten van mobiele sensoren voor het monitoren van de omgeving. Mobiliteitsbeperkend onderzoek in de computer wetenschappen heeft zich tot nu vooral gericht op het opheffen van beperkingen van de sensor.

De verwachting is dat o.a. door de opkomst van aan “smart phones” gekoppelde sensoren het gebruik van draadloze sensor netwerken de komende jaren sterk zal toenemen. Voordat het zover is zijn er echter nog veel vraagstukken die om nader onderzoek vragen, zoals de uitbreiding van de waarnemingsstrategie voor dynamische verschijnselen met inachtneming van mobiliteitsbeperkende omstandigheden, verbondenheid en data uitwisseling tussen sensoren, operationele toepassing van de ontwikkelende methoden in concrete omgevingstoepassingen en validatie van de ontwikkelde methoden.

RESUMEN

La creciente vulnerabilidad a los desastres naturales y la presión humana sobre los recursos naturales han incrementado la necesidad de observar y monitorizar el medio ambiente. La disponibilidad de información en tiempo real para una apropiada toma de decisiones es fundamental para proteger vidas humanas y recursos naturales. En este ámbito, las redes móviles de sensores, como por ejemplo las redes inalámbricas de sensores, prometen ser sistemas de observación capaces de obtener dicha información de una forma flexible y autónoma. Las redes móviles de sensores se componen de sensores geográficamente esparcidos muy cerca del fenómeno de interés. Estos sensores son autónomos, auto-configurables, pequeños, ligeros, con energía limitada y se transforman en sensores móviles cuando son acoplados a objetos móviles tales como robots, personas y bicicletas.

La investigación sobre redes de sensores móviles se ha centrado principalmente en la utilización de la movilidad de sensores para mejorar las principales limitaciones de una red de sensores como son la topología de la red, la conectividad y la conservación de la energía. Sin embargo, la utilización de esta movilidad para mejorar la monitorización del medio ambiente sigue siendo en gran parte inexplorada. Para abordar este reto es necesario considerar dos aspectos principales de la movilidad: el muestreo móvil y las restricciones a la movilidad. El muestreo móvil se refiere a *dónde* los sensores móviles se deben mover, mientras que las restricciones a la movilidad se refieren a *cómo* este movimiento debe ser manejado teniendo en cuenta el contexto en el que se realiza la monitorización. Esta tesis explora métodos de movilidad de sensores dentro de una red inalámbrica de sensores para ser utilizada en la monitorización medio ambiental. Para lograr este objetivo, cuatro sub-objetivos han sido definidos:

1- Explorar el uso de metadatos para describir los estados dinámico de las redes de sensores;
2- Desarrollar un modelo de restricciones a la movilidad para inferir comportamientos de los sensores móviles;
3- Desarrollar un método para adaptar el muestreo espacial utilizando sensores móviles restringidos;
4- Extender el método de muestreo desarrollado en el objetivo 3 para monitorizar fenómenos medio ambientales que son altamente dinámicos.

El Capítulo 2 explora el uso de metadatos para describir los estados dinámicos de las redes de sensores. Un modelo de contexto es propuesto para describir la situación general en la que una red de sensores está monitorizando.

El modelo se compone de cuatro tipos de contextos: del sensor, de la red, de la monitorización y de la organización. Cada uno de los contextos describe a la red de sensores desde una perspectiva diferente. Los metadatos, definidos como descriptores de los datos observados, configuraciones de sensores y funcionalidades, se utilizan como parámetros para describir lo que sucede en los diferentes contextos. Los resultados revelaron que la utilización de los metadatos es apropiada para describir el estado de una red de sensores considerando los diferentes contextos, y para informar sobre este estado a otros componentes, sistemas o usuarios.

El Capítulo 3 desarrolla un modelo que describe restricciones a la movilidad para ser utilizadas en la inferencia del comportamiento de sensores móviles. El modelo propuesto consta de tres componentes: primero, la tipología de contexto presentada en el Capítulo 2 es usada para describir las restricciones a la movilidad en los diferentes contextos; segundo, un grafo contextual, modelado como una red bayesiana, es usado para codificar dependencias entre las restricciones a la movilidad tanto dentro del mismo contexto, como entre contextos diferentes, así como también entre las restricciones y los posibles comportamientos; y tercero, reglas contextuales son usadas para codificar cómo se espera que las restricciones a la movilidad restrinjan el comportamiento de los sensores. Los metadatos que describen el fenómeno monitorizado y las propiedades de los sensores son utilizados para alimentar al grafo contextual, los cuales se propagan siguiendo la estructura del grafo, mientras que las reglas contextuales infieren el comportamiento más adecuado. El modelo fue utilizado para simular el comportamiento de una red de sensores móviles con el fin de obtener una cobertura espacial adecuada en situaciones de bajo y alto riesgo de incendio forestal. Se demostró que el modelo de restricciones a la movilidad exitosamente infiere comportamientos tales como dormir sensores, mover sensores, o desplegar más sensores para mejorar la cobertura espacial.

El Capítulo 4 desarrolla un método de muestreo espacial para ser usado con sensores móviles restringidos, el cual se basa en el valor esperado de la información (VEI) y las restricciones a la movilidad. El VEI permite tomar decisiones sobre la localización a observar de tal forma que se minimice el costo esperado de realizar predicciones erróneas acerca del fenómeno. Un criterio basado en la agregación espacial del VEI es propuesto. Las restricciones a la movilidad permiten tomar decisiones sobre qué sensor debe moverse. Un criterio de costo ponderado con la distancia a recorrer es propuesto para minimizar los efectos no deseados que la movilidad del sensor puede provocar en la red de sensores, como por ejemplo el agotamiento de la energía. Como forma de evaluación, el método fue comparado con una selección aleatoria de localizaciones de muestreo combinada con la selección del sensor a mover en base a un criterio de mínima distancia Euclidiana. Los resultados demostraron que el VEI permite seleccionar los lugares que son más informativos, mientras que las restricciones a movilidad proporcionan el contexto necesario para seleccionar el sensor que se moverá.

El Capítulo 5 extiende el método desarrollado en el Capítulo 4 para el caso de fenómenos muy dinámicos. El método decide cuándo y dónde tomar muestras de un fenómeno dinámico con sensores móviles. El criterio de optimización es la maximización del valor esperado de la información (VEI) de una nueva distribución espacial de sensores en un momento dado. El método fue demostrado con un ejemplo simulado en el que el incendio de una fábrica de productos químicos libera humo contaminado a la atmosfera. El penacho de humo varía en el espacio y en el tiempo debido a variaciones en las condiciones atmosféricas y podría ser sólo parcialmente estimado por un modelo determinista de dispersión. En este ámbito, las observaciones in-situ adquiridas por los sensores móviles se utilizan para mejorar las predicciones del modelo determinista. Como forma de evaluación, el método fue comparado con movimientos aleatorios de sensores y con la distribución espacial previa de los sensores, es decir sin realizar ningún movimiento. Los resultados pusieron de manifiesto que la utilización de VEI para optimizar la movilidad de sensores reduce exitosamente el riesgo causado por las predicciones parciales del modelo determinista.

El Capítulo 6 sintetiza los principales hallazgos y mis reflexiones sobre las implicaciones de estos hallazgos. El muestreo medio ambiental con sensores móviles es importante para seleccionar y observar las localizaciones que más contribuyen con la mejora de la calidad de las decisiones orientadas a la protección de vidas humanas y recursos naturales. Las restricciones a la movilidad son relevantes para gestionar la movilidad de los sensores una vez que la localización a observar ha sido decidida por el método de muestreo. La perspectiva tradicional en ciencias de la computación sobre las restricciones a la movilidad busca principalmente la auto-protección del sensor, en lugar de la protección de los seres humanos y los recursos naturales. En cambio, en el ámbito de la observación medio ambiental, los sensores móviles primordialmente deben mejorar la monitorización, incluso cuando dicha movilidad podría producir efectos negativos sobre la cobertura espacial, la conectividad o el consumo de energía. Por ello, las restricciones a la movilidad son útiles para reducir esos efectos negativos pero sin llegar a restringir el método de muestreo en sí mismo. Aunque las redes de sensores son actualmente una tecnología madura, su uso aún no está generalizado entre los expertos en geo-información y medio ambiente. El uso operativo de estas redes de sensores en las ciencias de la geo-información y del medio ambiente necesita, por lo tanto, ser promovido. Esta tesis se centra en las redes inalámbricas de sensores, no obstante otros tipos de redes de sensores informales también podrían ser relevantes para la monitorización medio ambiental, tales como teléfonos inteligentes, ciudadanía voluntaria y web de sensores. Por último, las siguientes recomendaciones son dadas para futuras investigaciones: extender el método de muestreo de fenómenos dinámicos para contemplar las restricciones a la movilidad; desarrollar métodos de muestreo siguiendo un enfoque descentralizado; focalizar en las restricciones a la movilidad relacionadas con la transmisión de datos y conectividad; llevar a cabo estudios para revelar preferencias sobre la movilidad restringida de sensores en diferentes tipos de aplicaciones medio ambientales; y validar los enfoques propuestos en aplicaciones operativas.

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About the author

CURRICULUM VITAE

Daniela Ballari was born on 13th of August 1980 in Colonia Bossi, a small village in the countryside of Santa Fe Province (Argentina). She finished her secondary education in the city of Morteros in 1997. In 2004, she obtained the diploma of Land Surveyor from the National University of Córdoba. While a student, she was appointed as assistant lecturer of Topography in the National University of Córdoba and she worked in the Cadastral office of Córdoba Province. From 2005 to 2009, she worked as a research assistant in the Technical University of Madrid (Spain). Her work was in collaboration with Spanish public institutions such as the National Geographic Institute, regarding: Spatial Data Infrastructures, standardisation, geo-information metadata and web mapping. She also was a guest lecturer in diverse countries such as Argentina, Spain, Ecuador, Cuba and Panama. During her stay in Madrid, she obtained the Diploma of Advanced Studies and started her PhD. In 2009, she moved to Wageningen (the Netherlands) to continue her PhD at the Centre for Geo-information and Remote Sensing of Wageningen University. Her research explored approaches for sensor mobility within a mobile sensor network to improve environmental monitoring.

Selected publications list

PEER REVIEWED PUBLICATIONS

Ballari, D., Wachowicz, M., Bregt K.A., Manso Callejo, M.A. (2012). Mobility constraint model to infer sensor behaviour in forest fire risk monitoring. Computers, Environment and Urban Systems 36, 81-95.

Ballari, D., Wachowicz, M., Manso Callejo, M.A. (2009). Metadata behind the Interoperability of Wireless Sensor Network. Sensors Journal 9(5), 3635-3651.

Ballari, D., de Bruin. S., M., Bregt K.A. (under review). Value of information and mobility constraints for sampling with mobile sensors. Computers&Geosciences.

Ballari, D., de Bruin. S., M., Bregt K.A. (under review). Expected value of information for sampling dynamic phenomena with mobile sensors. International Journal of Applied Earth Observation and Geoinformation.

CONFERENCE ARTICLES

de Bruin. S., Ballari, D., M., Bregt K.A. (2011). Multiphase sampling using expected value of information. Proceedings of the 7th International Symposium on Spatial Data Quality, ISSDQ 2011. Coimbra, Portugal.

Ballari, D., Wachowicz, M. (2010). The design of a Bayesian Network for mobility management in Wireless Sensor Networks. Proceedings of Giscience 2010. Zurich, Switzerland.

Ballari, D., Wachowicz, M., Manso Callejo, M.A. (2008). Metadata behind the Interoperability of Wireless Sensor Network. Proceedings of the International Workshop Sensing a Changing World 2008. CGI report CGI-08-005, Kooistra, L., and Ligtenberg, A., 2008 (eds.). Wageningen University and Research Centre, Wageningen, The Netherlands. ISSN 1568-1874, pp 116-119.

Ballari, D. Manso Callejo, M.A. Wachowicz, M. (2008). The Interoperability of Wireless Sensor Networks. Proceedings of GI-Day 2008: Interoperability and spatial processing in GI applications. Münster, Germany.

Ballari, D., Wachowicz, M., Manso Callejo, M.A. (2008). The Interoperability of Wireless Sensor Networks. Proceedings of GEOSS Sensor Web Workshop. Geneva, Switzerland.

Ballari, D., Sánchez Maganto, A., Nogueras-Iso, J., Rodríguez Pascual, A., Bernabé. MA. (2006). Experiences in the use of an ISO19115 profile within the framework of the Spanish SDI. Proceedings of the GSDI-9 – Global Spatial Data Infrastructure. Santiago de Chile, Chile.

PE&RC PhD Education Certificate

With the educational activities listed below the PhD candidate has complied with the educational requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE&RC) which comprises of a minimum total of 32 ECTS (= 22 weeks of activities)

Review of literature (5 ECTS)

- Wireless sensor networks and interoperability issues (2007/2008)
- Mobility in geo-sensor networks (2009/2011)

Writing of project proposal (4.5 ECTS)

- Dynamic interoperability of wireless sensor networks: contextual approach based on metadata elements (2009)

Post-graduate courses (7.1 ECTS)

- Advanced distributed applications of geographic information; Technical University of Madrid, UPM (2007)
- Publication of maps on the internet; UPM (2007)
- Methodology and scientific documentation; UPM (2007)
- Quality of cartographic data; UPM (2007)
- Bayesian statistics; PE&RC (2009)
- Basic statistics; PE&RC (2010)

Laboratory training and working visits (1.2 ECTS)

- OGC Sensor web enablement; training; University of Muenster; Sany project-6th framework programme (2007)
- Sensor interoperability and mobile sensors; visit; University of Muenster (2010)

Invited review of (unpublished) journal (1 ECTS)

- Computers, Environment and Urban Systems: Movement data (2011)

Competence strengthening / skills courses (2.9 ECTS)

- Course of voice and public communication; UPM (2008)
- PhD Competence assessment; PE&RC (2009)
- Coaching on effective behaviour in your professional surroundings; WGS (2010)
- Techniques for writing and presenting a scientific paper; WGS (2010)

PE&RC Annual meetings, seminars and the PE&RC weekend (1.8 ECTS)

- PE&RC Weekend (2009)
- PE&RC Day (2009)
- PE&RC Day (2010)
- SENSE PhD-day (2011)

Discussion groups / local seminars / other scientific meetings (6.2 ECTS)

- Spanish SDI working group (2007/2009)

- Spatial Methods Discussion Group (2009/2011)
- Maths&Stats Discussion Group (2009/2011)

International symposia, workshops and conferences (7.3 ECTS)

- GEOSS Sensor Web Workshop (2008)
- GI-Day: Interoperability and Spatial Processing in GI Applications (2008)
- Sensing a Changing World (2008)
- GIScience: Sixth International Conference on Geographic Information Science (2010)

Lecturing / supervision of practical's / tutorials (6.6 ECTS)

- Postgraduate course of spatial data infrastructures; 9 days; Technical University of Madrid, Spain (2007 and 2008)
- Course of experts in geographic information management; 2 days; University of Seville, Spain (2009)
- Videoconference: sensor networks and sensor web enablement; PhD lecture; 1 day; Technical University of Madrid, Spain (2010)
- Lecture in MSc course on geometrics: spatial data infrastructures and geo-sensor networks; 10 days; Azuay University, Ecuador (2011)