Abstract: Emerging wireless sensor network (WSN) technologies are opening up many important new opportunities for applications to the built environment, like traffic management, emergency response, and pollution monitoring. However, today’s WSNs have little or no spatial capabilities, and are primarily treated as simply a new data source for integration with other conventional spatial information systems. In contrast, this paper explores the potential for augmenting such networks with the capabilities to not only capture, but also process, query, and even use spatial data in the network itself. The objective is to embed spatial intelligence within the built environment using wireless sensor networks. This “ambient spatial intelligence” (AmSI) presents new fundamental research challenges to many established areas of geomatics and spatial information science. This paper identifies key research problems across geomatics, in the domains of positioning, geographic information science, spatial cognition and geovisualization, spatial data infrastructures, and integration with established data sources like remote sensing and photogrammetry. Using the example of monitoring native vegetation change, the paper indicates how each of these topics is required to contribute to a complete AmSI application to sustainable cities.

Keywords: geosensor networks, geographic information science, geovisualization, positioning, spatial data infrastructures, remote sensing, spatial cognition
**AMBIENT SPATIAL INTELLIGENCE FOR SUSTAINABLE CITIES**

**1. INTRODUCTION**

Emerging technologies for environmental monitoring are opening up many important new opportunities for applications to the built environment, like traffic management, emergency response, and pollution monitoring. In particular, wireless sensor networks (WSN, wireless networks of miniaturized, sensor-enabled computers) are capable of flexible, low-cost monitoring of a range of environmental parameters and phenomena at very fine levels of spatial and temporal detail.

However, today’s wireless sensor networks have limited or no spatial capabilities, and are primarily treated as simply a new data source for integration with other conventional spatial information systems. In contrast, this paper explores the potential for augmenting such networks with the capabilities to not only capture, but also process, query, and even use spatial data in the network itself. The objective is to embed ubiquitous spatial intelligence within the built environment using wireless sensor networks. This vision of “ambient spatial intelligence” (AmSI) presents new research challenges as well as providing new applications for existing research ideas.

This paper presents a “road map” for realizing ambient spatial intelligence for sustainable cities, proposing a research agenda for tackling the fundamental spatial problems across geomatics. Section 2 provides an overview of the state of WSNs, highlighting the key features and constraints presented by the technology. Section 3 examines how those technological constraints motivate fundamental research questions across many established areas of geomatics and spatial information science, including positioning, geographic information science, geovisualization, and spatial data infrastructures. Section 4 provides a concrete example of these challenges, by outlining a design for an example application of ambient spatial intelligence to sustainable cities. Section 5 concludes the paper with a summary of the findings of this paper, and an indication of research priorities.

**2. BACKGROUND**

Recent advances in wireless sensor networks have been driven by a range of underlying technological advances, primarily advances in new MEMS (micro-electro-mechanical system) sensor technology; wireless digital communications; and low-power mobile computing technology. Taken together, these technologies are allowing small-format, battery-powered, sensor-enabled computers, called “sensor nodes” or “sensor motes”, to be built at low cost. These sensor nodes have the capability to collect and process data about their immediate environment in real time, as well as communicate that data to other nearby nodes and computers.

Figure 1 shows an example of a wireless sensor node deployed in an urban park as part of a field study at the University of Melbourne. Such nodes have an on-board battery pack for power, a programmable microcontroller for controlling node behavior and processing data, wireless RF radio transceiver for communication, and an array of simple sensors, like light, temperature, humidity, and accelerometer. Although today these nodes can still be quite large (a few cubic centimeters), as the technology develops, much smaller nodes of less than cubic centimeter in size are planned (e.g., so-called “SmartDust” or “PicoNodes”, Kahn et al. 1999; Rabaey et al. [1999]).
In many applications, the location where data is sensed is critical to the meaning of that data. As a result, the term “geosensor network” (GSN) is often used to refer to WSNs that monitor environmental changes in geographical space (Nittel et al., 2004). The technology that underlies geosensor networks is rapidly developing, changing substantially year to year or even month to month. However, there are four fundamental features of geosensor networks that distinguish the technology from other spatial data capture/processing systems, and remain independent of technological advances:

1. Size: A GSN contains large numbers of sensor nodes: today tens or hundreds of nodes; in the future networks with thousands or millions of nodes are planned. Each node is able to autonomously sense, process, and communicate data about its environment.

2. Detail: As a result of the large numbers of nodes in a GSN deployed across relatively small spatial areas, a GSN can generate data at much finer levels of spatial and temporal detail than most conventional spatial data capture systems (for example, with nodes spacings less than 1m, and sensor sampling frequencies of less than 1 second).

3. Cost: Individual nodes in a geosensor network rely on mass-produced, low-cost construction. Although today nodes typically cost in the order of $100, as the technology matures, the objective is to build nodes for as little as $1.

4. Reliability: Because of the low costs of construction, the sensors on board each node, and the node itself, will normally be manufactured to relatively low specifications, poorly calibrated, and subject to faults and failures. In other words, low cost also implies low reliability for individual nodes. A key challenge in WSN is to use data fusion techniques to generate high reliability data from a network, even though individual nodes may be low reliability.

Figure 1 Wireless sensor node (iMote2) deployed as part of a pilot sensor network in urban parkland at the University of Melbourne
One further important feature of geosensor networks is the constraints on battery energy and communication. Batteries are the primary source of power for nodes in most GSN. In most applications, energy harvesting (such as from solar panels, vibration, or thermoelectrics) provides substantially less power than required by today’s wireless sensor nodes, and when compared with modern batteries. Although some ingenious solutions to such problems have been suggested (e.g., Rahimi et al. 2003), these are typically suited to particularly specialized applications (for example, where mobile robots can physically transport energy to needy nodes). The recent history of the development of power sources indicates that in the broad range of GSN application, limitations on power are likely to persist into the foreseeable future. Thus, limitations on energy resources are often also regarded as fundamental to geosensor networks.

5. Energy limitations: Untethered nodes rely on limited battery resources for all operations, including sensing, processing, and communication. However, communication is the most expensive operation, for example requiring more than 1000 times more energy to transmit a byte of data than execute a CPU instruction.

Ambient spatial intelligence (AmSI) involves the use of ubiquitous, low-cost GSNs, in combination with conventional spatial data sources and information systems, to embed into built and natural environments the intelligence to monitor spatial changes and respond to spatiotemporal queries. The vision of ambient spatial intelligence has its roots in the visions of ambient intelligence (AmI, Ducatel et al. 2001) and ubiquitous computing (UbiComp, Weiser, 1993). However, incorporating spatial capabilities into AmI and UbiComp presents a range of fundamental research challenges, specific to geomatics and spatial information sciences. The following section examines in more detail those changes.

3. KEY RESEARCH CHALLENGES

This section identifies and details the key research challenges facing the development of AmSI applications. These challenges relate to classic research topics across geomatics. As a result, the section looks in turn at five main areas: positioning; geographic information science; spatial cognition and geovisualization; spatial data infrastructures; and integration with existing data sources, in particular remote sensing and surveying.

3.1 Positioning

Positioning is defined as the process of measuring or computing the two or three dimensional coordinates of an object. Conventional manual surveying the location of nodes is not appropriate for GSN, because of a) the increasingly large size of networks (moving towards thousands or millions of nodes in a network, see Section 2); and b) nodes in a GSN may be mobile, either attached to some moving objects, like a vehicle or person, or capable of their own movement.

Consequently, nodes in a GSN must be capable of computing their own position (termed “self-localization”). A wide range of literature has already begun to address the challenge of self-localization in WSNs (e.g., Langendoen and Reijers, 2003). Conventional localization technologies, like GPS, are also currently not well-suited to use in GSN in many cases for two main reasons, specifically:
• **Heterogeneous environments:** GSNs must operate in a range of heterogeneous environments, including indoor and outdoor environments, in urban canyons, and under dense tree cover. Signal attenuation and multi-path problems mean in many cases GPS cannot support these requirements.

• **Accuracy:** While GPS can provide high levels of absolute accuracy, relative accuracy is often important in dense GSN deployments with node spacings of a few meters or less. Reliably generating relative positions of nodes in such situations presents challenges to GPS technology, especially given the need for low power and low cost hardware.

Although GPS research is currently addressing each of these problems, it is unlikely that GPS or any single technology can provide a complete positioning solution. Instead, a mix of positioning systems is certain to be required in most cases. For example, integrating GPS and accelerometers can help to provide positioning based on GPS in mobile environments, where GPS fixes can be augmented with dead reckoning techniques.

Thus a key geomatics research challenge for AmSI is to develop ubiquitous positioning systems that are capable of reliable, low-power self-localization in a range of environments using low-cost hardware.

### 3.2 Geographic information science

Spatial information systems like geographic information systems (GIS) and spatial databases are the primary technologies for storage, processing, and querying of spatial data. However, these technologies have some important limitations when applied to GSN:

• **Static data:** Spatial information systems are primarily designed to deal with static data or sometimes with dynamic data that is relatively infrequently updated (e.g., moving object databases, Güting and Schneider 2005; Wolfson and Mena 2005). However, the highly dynamic data generated by GSN presents major challenges to the data models and data structures currently used in spatial information systems, for example in generating explicit representations of geographic events and processes, like “traffic jams” or “urbanization” (cf. Worboys, 2005).

• **Centralized data:** Almost all of today’s spatial information systems assume a centralized approach, where spatial data is centrally collated and stored before subsequent processing. However, in a GSN relying solely on a centralized architecture leads to information bottlenecks, single points of failure, and high latency with real-time data. Energy limitations in particular present major constraints to wireless communication: processing information requires much less energy than communicating information, making in-network information processing especially important in GSN. Thus, a fundamental challenge posed by GSNs is to develop the capability to support spatiotemporal queries and detect spatial events in the network itself (Worboys and Duckham, 2006).

For example, consider a GSN monitoring the evolution of an environmental pollution event in an urban environment. In such a situation, queries like “When does the pollution spill start breaking up/dispersing?” could help the recovery management effort. Efficiently satisfying such dynamic queries requires both the ability to model geographical events, like the break up of a region of high pollutant concentration, and...
the ability to efficiently detect such spatial events by processing real time data in the network itself, without relying on centralized collation of sensor data.

The problems of static data and centralized data processing combine in the provision of real-time information about urban environments, for example real-time travel information. Static databases may have information about time tables or typical traffic counts at particular times of the day, but have limited capabilities to represent and distribute real-time information, such as current running times of buses, trains, or taxis. For individual data about large numbers of mobile objects, centralized architectures form a bottleneck for both the collection of this data (tracking) as well as for the distribution of information based on this data (e.g., route planning).

In this scenario, mobile GSN offer the potential for better information collection and provision. Local ad-hoc communication between mobile and static nodes can be used for traffic flow coordination, ride planning, travel time prediction, mobile robot control and more (e.g., Dillenburg et al. 2002; Wolfson and Xu 2004; Winter 2008).

As a result, in the domain of geographic information science, a key challenge is to develop new algorithms and data structures that can enable efficient in-network processing of dynamic sensor data in both static and mobile networks, providing the intelligence for AmSI. These algorithms and data structures must support both state-oriented queries (about the state of world at a particular time, e.g., “Where is the pollution spill now?”); and event-oriented (about changes in the world, e.g., “How fast is the pollution spill growing?”).

3.3 Spatial cognition and geovisualization

GSN are an example of new spatial data capture technologies capable of generating extremely high volumes of data. High data volumes are also generated in other domains, notably remote sensing. In all such cases, the key problems facing communication of data to humans are:

- **High dimensionality**: The data generated by GSN has very high dimensionality, making it especially difficult for humans to interpret. The data typically comprises a large numbers of sensors, each of which is generating data about an array of sensed phenomena (e.g., temperature, light, humidity, CO2 concentrations, ...) in two or three spatial dimensions with frequent updates over time (potentially several updates a second).

- **Identification of salient patterns**: The high volumes of data can overwhelm users, making identification of meaningful patterns within raw data extremely difficult. Further, the raw measurements of sensed data are typically only meaningful to technical experts and need to be further processed in order to be more generally useful (e.g., “5000ppm CO2”, versus “high” or “toxic” levels of CO2).

- **Location-based and mobile data access**: As the information is being generated about real time changes, there are clear advantages to making this information available to observer in the field. Such users might need to gather data from the sensors in their neighborhood and be supported by visualization of this. Mobile users could then progressively extend and revise their knowledge as their locations change. For example, in the urban context we can consider sensors accumulating temperature and sound data. An urban designer equipped with wearable computer and an augmented reality head mounted display would collect data while moving within an environment in
need of climatic or acoustic remediation.

There has been rapid development in recent years of processes of geovisualisation to help deal with these issues and to help humans to make sense of this data (Dykes et al, 2005). These developments have been aided by the rapid development of computer processing power and, particularly, by the rapid emergence of graphic processors which deal with many aspects of three dimensional presentation in hardware and support real-time exploration of complex data spaces (Dollner, 2005).

However, by their distributed nature and constraints on communication GSN present a wholly new challenge. New techniques are required for preprocessing spatial data, in particular identifying fundamental spatiotemporal concepts that are meaningful to humans (like merging/splitting, appearance/disappearance of geographic regions, cf. Klippel et al, 2008). After intelligent data processing to identify key spatial or temporal anomalies, geovisualization support for improved visual and spatial thinking would help the designer to more easily integrate highly dynamic, multidimensional data. As a further stage, the real-time sensor data might be integrated with environmental modeling, including the option of changing the geometry of the environment interactively. Finally, using virtual reality systems there will be the capacity to present the information via the augmented reality interface (Azuma et al, 2001) placing the dynamic data in an understandable context of life-like scenes (Goldsmith et al, 2008). As a consequence the designer would be able to test options from both aesthetic and comfort perspectives simultaneously, within the real-world context and with the option to compare model results with real-world measurements.

Other issues include integration with existing imagery-based data sources. Imagery often requires high level processing and human interpretation. There are challenges both in designing optical sensors which can provide useful data within an AmSI model, and in integrating data from such a network into conventional remote sensing data sets. Approaches such as “single pixel sensors” and real time ground verification need to be developed. This need will grow acute as remotely sensed imagery (both aerial and satellite) continues to become a ubiquitous backdrop for spatial visualization.

### 3.4 Spatial data infrastructures

Research into spatial data infrastructures (SDIs) is already beginning to focus on the impact of new technologies like GSN. Integrating AmSI into national and international SDIs requires mechanisms for sharing and processing dynamic data across highly heterogeneous GSN, making it available in different forms to a wide range of organizations in diverse applications. SDIs make it possible to integrate GSN data with a wide range of other data such as land tenure, land parcel and land ownership data, valuation, land use planning, and other data sets that are central to the management and administration of cities. A number of critical research challenges exist:

- **Integration and use of GSN within SDIs**: The availability of GSN data opens many opportunities to integrate this data with diverse data sets within SDIs to broaden the scope of AmSI such that this data can be integrated with ownership, valuation and land use planning data for example. However this presents many research challenges if useful policy outcomes for the management of cities are to be achieved.

- **Data quality**: Conventional spatial and land information systems are primarily
designed for use with high quality spatial data, where data can be subjected to rigorous quality control procedures. By contrast, individual low-cost nodes in a GSN can be highly unreliable, even if the network as a whole can provide more reliable information. Effectively communicating the quality of spatial data sources to decision makers is a long-standing research problem, made more urgent by the dynamic and heterogeneous nature of GSN.

- **Spatiotemporal semantics**: SDIs support the integration of information from many different GSN, monitoring different phenomena, possibly even within the same areas. Understanding and integrating this information requires clear and unambiguous specifications of the semantics of the information generated. For example, even for an observation of temperature, simply knowing whether temperatures are measured in Celsius or Fahrenheit, updated every second or every day, whether the data item was generated by a single node, or by multiple nodes over an area, can all be central to understanding the meaning of that data item.

- **Privacy**: For some AmSI applications, the monitored information may refer to individuals, and so present important privacy implications. In particular, applications where nodes are associated with vehicles or even individuals present difficult location privacy issues, where collection and dissemination of an individual’s location can seriously compromise that person’s right to control information about him/herself. SDIs and particularly land information such as land registry or land ownership data has a long history of dealing with privacy issues and as such can provide a framework or guidance on privacy issues.

As a result, research challenges in the SDIs domain include research into integration and wide dissemination of AmSI data, for example using the Sensor Web (Delin et al, 2005); development of spatiotemporal ontologies for encoding the meaning of GSN data in a form suitable for automated reasoning about heterogeneous sensor data; and research into techniques for protecting location privacy, such as anonymization and obfuscation of data.

### 3.5 Integration with existing data sources

Information generated by a GSN complements, but does not replace established centralized data sources, like remote sensing and surveying. Where traditional centralized data sources offer higher reliability and cover larger spatial extents, information from decentralized GSN can provide unprecedented levels of spatial and temporal detail. Bridging the gap between different spatial and temporal granularities and extents, demands new techniques for integration of centralized and decentralized information sources. In addition to the different spatiotemporal semantics of AmSI data, the key problem facing information integration is connecting the different spatial and temporal granularities of existing data sources:

- **Multi-granular data**: As already highlighted, GSN are able to generate data at much finer spatial and temporal granularities, although typically over small spatial extents (e.g., currently up to a few square km). As a result, integrating this data from a GSN with data, such as remotely sensed data, presents substantial problems with widely different spatial granularities as well as temporal granularities (updates for centralized data sources are typically of the order of years, where updates may be every few seconds in a GSN).

To address the problem of integration of existing data sources in AmSI, multi-
granular geographic information fusion techniques are needed (e.g., Duckham and Worboys, 2006), as well as work in spatiotemporal ontologies already identified. One approach to this problem may be to change the way in which satellite image data are considered and to regard the whole extent constellation of imaging satellites as itself constituting a mobile wireless network of global scope. Conventional remote sensing treats each image as a unique data set but each image is in reality only part of a data series collected over the same area by different sensors and with different spatial and temporal granularities. While very different from the current spatial and temporal paradigms of remote sensing, multi-granular geographic information fusion techniques may be valuable not only in integrating mobile network data into conventional remotely sensed data sets, but also in making better use of those remote sensing data sets themselves.

4. AMSI IN SUSTAINABLE CITIES

The previous section sets out some of the key spatial challenges in developing AmSI applications. This section, surveys some of the potential roles of AmSI in sustainable cities, and looks in more detail at one specific application: monitoring native vegetation.

<table>
<thead>
<tr>
<th>Application</th>
<th>Network deployment</th>
<th>Key spatial challenges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermal monitoring</td>
<td>Dense, city-wide network of simple sensors, monitoring temperature fields across the city</td>
<td>- Node localization&lt;br&gt;- In-network identification of extended spatial events&lt;br&gt;- Multi-granular integration with existing remotely sensed data</td>
</tr>
<tr>
<td>Traffic monitoring</td>
<td>Personal and in-vehicle sensors, exchanging information about road and traffic conditions</td>
<td>- Node localization&lt;br&gt;- Location privacy&lt;br&gt;- Location-based and mobile data access&lt;br&gt;- Identification of salient patterns (like traffic jams)&lt;br&gt;- Highly dynamic data</td>
</tr>
<tr>
<td>Land use and regulation</td>
<td>Targeted networks of sensors monitoring land parcels with particular regulatory and license restrictions (e.g., pollution and dumping)</td>
<td>- Integrating with SDIs (using dynamic spatial data for policy development and permit and license monitoring)&lt;br&gt;- Data quality&lt;br&gt;- High data dimensionality</td>
</tr>
<tr>
<td>Urban park and vegetation monitoring</td>
<td>Groups of networks monitoring, each targeted at monitoring vegetation changes in particular sensitive environmental or parklands</td>
<td>- High data dimensionality, many different sensed variables&lt;br&gt;- Data quality, and filtering sensor noise&lt;br&gt;- Integration with conventional mapped data sources</td>
</tr>
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</table>

Table 1 Example AmSI application in sustainable cities

Table 1 shows four example AmSI applications to sustainable cities, highlighting the
range of different uses, deployments, and spatial challenges. For example, thermal
monitoring of urban environments could be supported by dense WSN of simple
nodes with temperature monitoring capabilities. The key spatial research challenges
in developing such applications include efficient algorithms for in-network
identification of extended spatial events, like the emergence of “hot spots”; and
localization of individual nodes in urban canyons. On the other hand, traffic
monitoring can be supported by networks attached to mobile people and vehicles
monitoring weather and traffic condition. Such applications again face node
localization challenges, but additionally bring issues with location privacy of
individuals, and delivering real-time, location-based information about traffic
conditions to mobile individuals. Similarly, land use and natural resources monitoring,
pose different problems. The following subsection examines in more detail a specific
element, which includes issues related to environmental monitoring and urban
policy.

4.1 Example: Monitoring Native Vegetation Clearance

To illustrate the role of the different research challenges, this section presents an
example of AmSI applied to sustainable cities. The example scenario is of using
AmSI to monitor native vegetation clearance in urban environments. In Victoria,
Australia, two thirds of the state’s native vegetation has been cleared, with 60
percent of native vegetation types on private land threatened with extinction (DNRE,
2002). Similar declines are found in proximity to large urban areas around the world.
As a result, protection of native vegetation in urban environments forms an important
component of Victoria’s strategy for sustainable cities.

However, today a key barrier to protecting native vegetation in sustainable cities is
the lack of up-to-date, fine-detail spatiotemporal information about vegetation
changes in the state. Conventional change detection technologies, like remote
sensing, are ideal for covering large spatial extents at coarser levels of detail, but are
not economically viable for native vegetation monitoring at finer levels of detail.
Change detection technologies, like LIDAR and aerial photography, can provide very
fine spatial detail about vegetation change, but are typically used over smaller spatial
extents, and like remote sensing, are not well-suited or cost-effective for regular and
frequent updates, monitoring changes over the course of a day, for example. As a
result, we are currently investigating the use of GSN, embedded in urban
environments, to provide detailed information about urban vegetation change. GSN
can be deployed to monitor sensitive areas of vegetation, around rivers, water
courses, and urban parks. Further, native vegetation clearance in Victoria is covered
by permits, so deployments of GSN could be targeted at monitoring compliance with
permits in those areas.

Depending on the specific deployment details, a GSN of approximately 1000 nodes
would potentially cover an area of almost 10 square kilometers. The sensors can
monitor a range of environmental variables, such as (photosynthetic) light levels,
temperature, and humidity. Initial field tests have indicated that even such simple
sensors when deployed densely are capable of identifying vegetation clearance
when it occurs (for example, the “buffering” effect of vegetation means variability in
temperature and light levels over the course of a day are much greater following
vegetation clearance). However, more sophisticated sensors might also be used,
such as microphone sensors monitoring for sounds of clearance, such as chainsaws.
Such GSN could potentially form the basis for an AmSI system, generating
information about native vegetation clearance, which when combined with other
information about broad-scale vegetation changes, and urban zoning and permits.
could provide the basis for more active management of vegetation change, as well as for permit compliance. However, developing such an AmSI application requires answers to all of the research challenges already highlighted, and summarized further below.

**Heterogeneous environments (Positioning)**

Positioning thousands of nodes using conventional surveying is not scalable or economic. Further, urban canyons and vegetation cover inherent in the application means that while GPS may work in some cases, it cannot be relied upon to provide a complete localization solution. As a result, the application requires GPS to be complemented with other localization techniques, such as RF or ultrasound range-finding.

**Accuracy (positioning)**

The location of vegetation clearance is critical to any responses to that clearance. For example, a permit to clear native vegetation specifies the location in which clearance is permitted. Achieving an accuracy of localization that enables the GSN to determine reliably when clearance has extended beyond the permitted bounds is central to any compliance capability of the system.

**Static data (GIScience)**

Like any GSN deployment, the information concerning changes in vegetation is inherently dynamic. In particular, the application requires the capability to reason about event-oriented models of change, in particular identifying when a clearance event has occurred. Thus, the system must go beyond generating simple “snapshots” of the vegetation levels at particular times, to identifying what events have occurred in a region. In relation to the sampling theorem, the local knowledge bases of the GSN nodes need to have in-built concepts of spatial and temporal granularity and salience to robustly identify a change and separate from noise.

**Centralized data (GIScience)**

Most of the data generated by the application will be of little or no interest to decision makers, since it is expected to primarily confirm that there has been “no change” in an area over the course of a day or a week. Communicating such voluminous but low-value data to a central store represents a substantial waste of resources, and will have practical consequences in dramatically reducing the useful life of the GSN (before batteries run out). Consequently, the GSN must have the intelligence to identify important spatial changes in the network itself, using on-board processing and communication capabilities, without the need to relay all data to a centralized store. This processing may be based on ad-hoc or permanently set up local teams, or hierarchies of nodes. Furthermore nodes need a local awareness of what is salient and what level of information aggregation is appropriate to the application of vegetation clearance.

**High dimensionality (Spatial cognition and geovisualization)**

The data generated by the application will comprise sensed variables like temperature, light, humidity, over a period of months or years, over thousands of spatial locations. In making sense of such data, efficient tools for summarizing and visualizing changes are essential. For example, linking the data with virtual reality
visualization would help to provide concise and real-time overviews of changes to decision makers.

**Location-based and mobile data access (Spatial cognition and geovisualization)**

A multitude of wayfinding applications emerge in this scenario. Ecologists need to find patches of native vegetation within their tasks to make decisions on permits or to monitor clearings. Eco-tourists or green action groups may want to find rare native species in the urban environment (and having reached the location, detailed information about the species and the niche). Mobile robots might be deployed for plant maintenance in places difficult or dangerous to reach by people. In all these cases, patches of vegetation in urban environments are frequently hidden and hard to find. GSN can provide a wayfinding infrastructure by peer-to-peer communication with the visitor's mobile device. As soon as a visitor is close enough to be in radio range of one of the GSN nodes two types of services can be imagined. Pull services allow visitors to query nodes for their exact position; information that can be used to determine local orientation, or to be integrated with the mobile device's spatial dataset for routing and augmented visualization. Push services allow sensor nodes to advertise their presence to interested passer-bys, for example when they are at attractive patches of vegetation, or when they call for some intervention.

**Salient patterns (Spatial cognition and geovisualization)**

As indicated above (centralized data), in-network processing of data is needed to filter out irrelevant data, such as no change. However, further visualization tools are also needed to help users to identify salient changes (such as permit violations) or patterns in changes (such as areas at high risk of illegal clearances). Visualization tools can be deployed in-situ or remotely. In-situ augmented reality can be used to find patches or particular plants, and to visualize local changes for decision making. A clear communication to the decision maker, within the limits of positioning and spatial data quality, is one challenge. For remote visualization tools, based on maps or virtual reality, scale will be an issue, since the fine granularity of vegetation patches, the local generalization of observations within the GSN, and the large scale of the urban environment challenge traditional visualization methods for monitoring and decision making.

**Integration and use of GSN within SDIs (SDIs)**

The ability to integrate GSN data with a wide range of data available through SDIs increases the potential to use the data for worthwhile or beneficial decision making or policy outcomes. For example to be able to relate sensed variables such as light, temperature, humidity or vegetation to ownership, land use or valuation of a property can provide valuable insights into improved land management.

**Data quality (SDIs)**

In addition to positional accuracy, discussed above, information about how up-to-date sensed data is; how reliable it is; and how it relates to other data sources to be integrated with the GSN data, such as data from remote sensing and site visits, are all important in understanding the data generated, and as well as how it relates to the development of new policies for native vegetation protection.
Spatiotemporal semantics (SDIs)

There is a substantial gap between stated policy objectives, such as increasing the levels of native vegetation in urban areas, and the underlying GSN data, such as changes in temperature and light levels. Spatiotemporal ontologies are needed to help bridge this gap, and enable automated reasoning about a range of low-level sensor data from different sources, along with a linking of this data to broader policy objectives.

Location privacy (SDIs)

Although the GSNs are monitoring vegetation changes, potentially this information may need to be collected from private land (naturally with land owner’s consent) and may lead to identification of organizations or individuals who have failed to secure the correct permit for a clearance act. It is essential that systems exist to safeguard the rights to privacy of individuals. Collection of other sensitive information, such as locations of individuals or information about activities other than those that have an impact on native vegetation, is to be avoided.

Multi-granular data (Integration)

GSNs can provide fine-grained spatiotemporal information about vegetation change, targeted at specific sensitive or at-risk areas. However, a complete AmSI application also requires the integration of broader scale monitoring at coarser granularity, including remote sensing, aerial photography, and LIDAR information. This information will typically be at different spatial and temporal granularities, as well as covering larger extents that the GSN data.

5. CONCLUSIONS

This paper has set out the vision of ambient spatial intelligence, and a road map for research into AmSI that cuts across traditional boundaries within geomatics, requiring concerted research efforts across the discipline. The paper has identified key research problems according to the main topics within geomatics, positioning, geographic information science, spatial cognition and geovisualization, spatial data infrastructures, and integration with established data sources like remote sensing and photogrammetry. Finally, the paper shows, using the example of monitoring native vegetation change how these topics, are all required to contribute to a complete AmSI application to sustainable cities.

Despite the breadth of research needs to be addressed for AmSI, the key issues in most cases relate to long-standing research problems in geomatics, including research into:

- Uncertainty: the tools and techniques for processing uncertain geographic information, and representing the quality of spatial data;
- Granularity: the fundamental role of scale in geographic information, and the representation and integration of data about the same geographic area at different scales;
- Dynamism: the need to move beyond “snapshot” models of geographic information, towards explicit representation and processing of dynamic entities, like events and processes;
• Algorithms: the data structures and processing routines for transforming and linking geographic information sources;

• Visualization: the importance of intelligent real-time visual interfaces to support improved communication of multidimensional geographical information to decision makers;

• Social issues: the role of geographic information in society, and its importance to a broad range of government policies and activities.

Although the research agenda outlined in this paper sets out a “big picture” for concerted research in geomatics over the coming decade, current work is already beginning to address these issues. Specifically, related work by the authors is already developing some of the tools required to deploy a GSN capable of monitoring changes in native vegetation, in particular focusing on the issues of ubiquitous positioning, and in-network (decentralized) processing of geographic information.

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REFERENCES


**Presenter Biography**

Ian Bishop is a Professor in the Department of Geomatics at the University of Melbourne. His background includes aspects of visual landscape assessment and visual impact modelling using GIS and visualisation technologies. Current research concerns the development of game engine based visualization tools and the application of visualization to environmental decision making.