Farming the Web of Things

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An experimental smart farm uses environmental sensors, livestock monitoring technologies, and an ontology-enabled architecture for personal alerts and data sharing.

Primary industry in Australia has a proud record of both remarkable productivity and investment in innovation. The combine harvester, for example, revolutionized broad-acre crop production after its first commercial production in Australia in 1885. Today, there are new economic pressures driving a new round of information-based innovation, this time aligned with the technology push called the *Web of Things*. Since 1999, it has been mandatory for all Australian farmers to affix passive RFID ear tags to their cattle and to report movements between farms to a national database. Now, the first commercial systems for on-farm livestock location tracking are emerging; the Taggle system, for example, triangulates wireless signals from active ear tags as they are received at base station antennae. A national broadband network is being developed to deliver telephony and high-speed broadband to all Australian homes, schools, and businesses, including rural farms. Farming "things" are becoming electronically identifiable and measureable, but the "Web" that connects and adds value is largely unexplored.

The Australian farming sector includes more than 130,000 farms, most of which are operated on location as family businesses.[1] Smart phone apps are playing an increasing role on farms for both crop and livestock management.[2] Mobile phones and landlines are also the gateway to Web services, and farmers are as likely to take up Internet services as city residents.[3] We're developing a smart farm near Armidale, New South Wales, to be a technology-intensive property of the future.[4] Our experiments with fine-scale sensing technologies at Kirby Farm are improving the primary producer's situation awareness and thus contributing to on-farm productivity.

Here, we present our research on this prototype smart farm from two perspectives. First, we offer a technology perspective, outlining our semantic sensor network and its capability for generating alerts for conditions that augment local knowledge with physical measurement. We also discuss our recent evaluation of this effort, with performance measurements that demonstrate its feasibility in practice. Second, we review Australian agriculture's social and business context, which drive a business model that would enable the adoption of such technologies. We propose that, given imperative changes to the industry structure, the aggregation of farm-scale data creates opportunities for industry optimization that justifies the investment.

Figure 1. A soil sensor node on Kirby Farm near Armidale, New South Wales, Australia. The node is powered by a solar panel on top. A strong post keeps the electronics above any livestock, while carrying a wire to the sensors embedded in the soil a metre to the side.

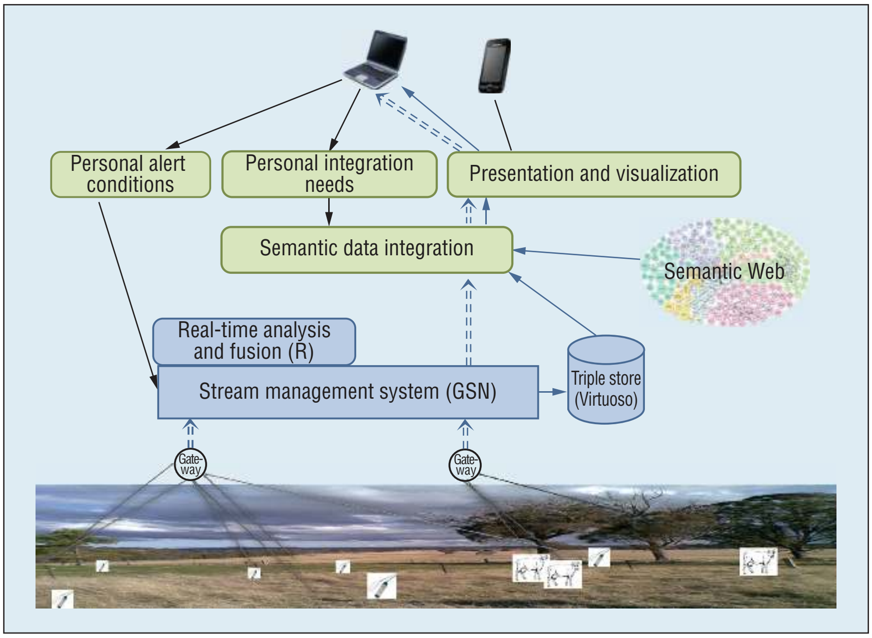

Figure 2. The architecture of the smart farm situation awareness and open data framework. Sensor data are data pushed to a stream management system that's extended with predefined analytic functions and dynamic alert conditions. Semantic Web technologies are used to define the alert conditions and to integrate and publish data. (Embedded Linking Open Data [LOD] cloud image courtesy of Richard Cyganiak and Anja Jentzsch.)

Technology

Kirby Farm is located on a 171.3 hectare (ha) livestock property typical of much of inland eastern Australia. Productivity of the sheep and cattle enterprises is dependent on managing pasture and forage crops, which provide the main feed source for the livestock. To determine landscape variability, we undertook a survey comprising an electromagnetic induction (EM38) soil scan, digital elevation mapping, and a pasture biomass (active optical sensor) scan, with corresponding spatial clustering analysis. We then installed 100 soil sensor nodes, each representing a locality of approximate homogeneity, and two above-ground weather station nodes.

As Figure 1 shows, each soil node has a Decagon 5TE soil moisture sensor, buried at a depth of 0.20 meters, that measures moisture, temperature, and electrical conductivity (ECa, which is correlated with salinity, soil moisture, and clay). It also has an Apogee ST-100 air temperature sensor at 2.4 m above the ground. The Vaisala WXT520 weather stations measure air temperature, humidity, and pressure; wind speed and direction; and rainfall and hail. Collocated on the weather station nodes are Apogee SP-110 solar radiation sensors. All nodes are CSIRO sensor hubs powered by solar panels with built-in sensors for solar voltage, solar current, battery voltage, and battery current. The sensor nodes form a wireless multihop network, which allows them to communicate back to a Linux gateway located in the shearing shed. From there, data is pushed via the public 3G cellular network to an installation of the open source Global Sensor Network (GSN) stream-processing middleware.[5]

Data Management

Figure 2 illustrates our approach to managing both live and persistent smart farm sensor data.

GSN is fed with the sensor data collected from the farm. In addition, Taggle cattle-location data is fed in by polling a website. Virtual GSN sensors are used to provide enhanced streaming output for further processing. Through these virtual sensors,

- summaries of sensor data are translated to RDF and persisted in a Virtuoso triple store;
- various algorithms, implemented in Java or R, are deployed to consume real-time sensor data and produce value-added streams; and
- semantic event descriptions are processed to generate alerts.

The smart farm control portal lets farmers develop personalized event descriptions in terms of an ontology designed for their farm. The descriptions are composed and handled via an extension of Taylor and Leidinger's method,[6] whereby users are guided to create class descriptions and class and property instances that together describe an event of interest. Event descriptions can include

- thresholds on data properties arising from sensors and virtual sensors, and

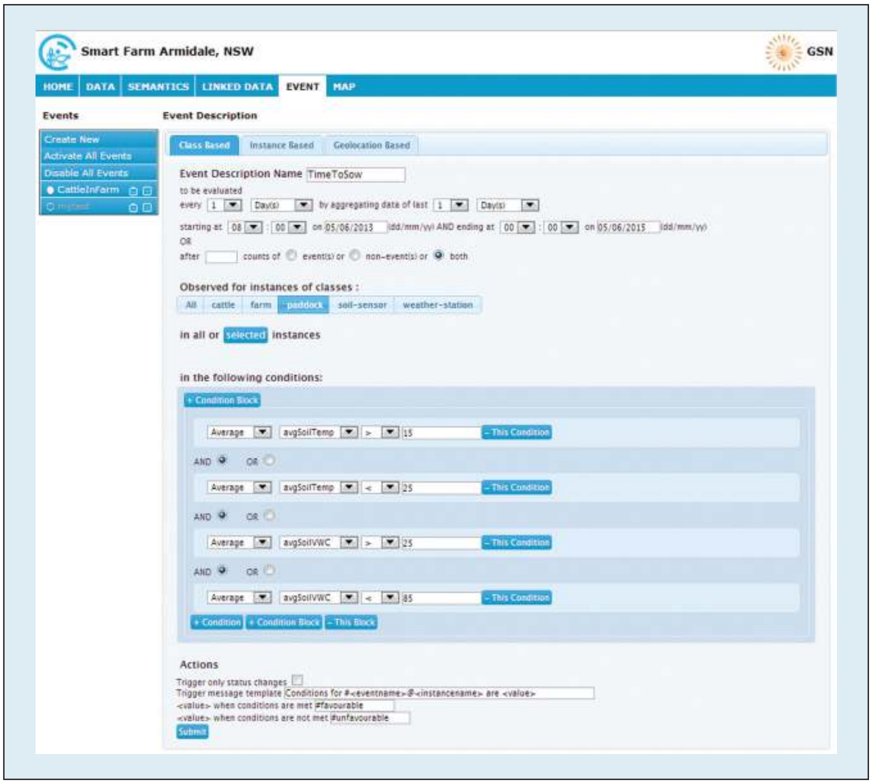

Figure 3. The time-to-sow event description. The description is enacted as virtual sensor nodes in the Global Sensor Network (GSN).

- temporal relationships among component events, such as exceeding thresholds over multiple streams within a set time period.

In this extension, simple Description Logic (DL)-safe rules, with conjunctive DL terms in the head, are expressed as Semantic Web Rule Language (SWRL) and are compatible with the W3C's Rule Interchange Format-Basic Logic Dialect (RIF-BLD) recommendation. The rules enable the co-reference of variables throughout the event description that cannot be expressed in Web Ontology Language-DL (OWL-DL), such as relating soil temperature and air temperature over the same paddock at the same time, and binding values of measurements to properties of the alert instance. DL reasoning is used for some optimization, but ultimately the event descriptions are translated to virtual sensor specifications in GSN for enactment, rather than being directly enacted through a semantically aware technology. When an event is detected by GSN, the relevant data is immediately inserted in the triple store, as assertions of an instance of a conjunctive RIF-BLD rule head. This approach means that we can, in principle, utilize any off-the-shelf stream processor without special semantic services for high-throughput event detection, and allocate our limited resources for persistent storage in the triple store to derived data of value instead of frequent raw measurements.

The RDF data is described using the Semantic Sensor Network (SSN) ontology of the W3C SSN Incubator Group[7]; the W3C Government Linked Data Working Group's RDF Data Cube vocabulary; and some local ontology extensions similar to those we did for climate data publishing.[8] We present an example of a SPARQL 1.1 query that compares daily maximum air temperatures on Kirby Farm with the historical record for locations in the same meteorological district as our farm's weather stations at http://smartfarm-ict.it.csiro.au/sparql-doc/compare-farm-and-archive-observations.html. The example uses other publicly linked data from the Australian Bureau of Meteorology[8] and demonstrates the ability to live-link the farm data to the Semantic Web's open government data. This is a formal query that can be executed on one of the many Web SPARQL endpoints. Alternatively, GUI-driven technologies to exploit such linking abound.

Performance

We've developed some scenario-based alerts to evaluate the runtime performance. Here, we present results of semantic alert processing over enriched streams as an indication of the technical success of the farm environment architecture. We use the "time-to-sow" alert, designed to assist with the optimal timing for sowing of oats for fodder, taking account of soil and weather conditions. We selected this alert as an example of a challenging event computation, as it's mapped to an event processor for each of 55 paddocks, each of which requires an R evaluation over two properties of several soil sensor streams. Figure 3 shows the description of the event through the smart farm control portal.

The event descriptions are enacted as virtual sensor nodes in GSN. We evaluated runtime performance by processing the 55 paddock event threads in parallel, with intervals of five minutes (the approximate time it takes for data from each sensor to be pushed from the field). As Figure 4 shows, we used a 64-bit Windows 7 desktop environment with Intel Core i5-3570 CPU with 3.4 GHz and 4 Gbytes RAM; in the figure, each line represents one of 55 paddock time-to-sow virtual sensors.

The data is collected over 60 time points. Because R is single-threaded, the event processing for each paddock must execute sequentially, which is reflected in the time taken at first. During the first event evaluation, the event threads are randomly delayed to avoid simultaneous access of R in consequent runs. On average, an event evaluation takes 357.73 milliseconds with a standard error of mean (SEM) of 15.19 milliseconds. Therefore, 168 events can be processed every minute on average. These events are compute-intensive compared to most tasks, such as comparing multiple sensors with threshold values executed with an average of 51.6 milliseconds and SEM of 9.4 milliseconds (that is, 1,162 events per minute).

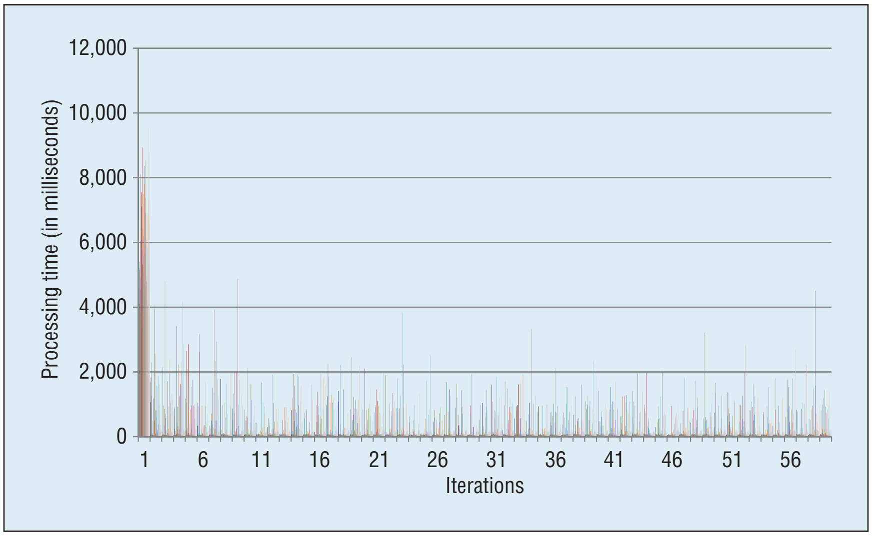

Figure 4. Performance evaluation of event processing. Each line represents the time taken in milliseconds to execute a time-to-sow virtual sensor for one of the 55 paddocks.

The Business Challenge

The publication of data like this creates an opportunity to connect Web of Things agriculture data services to food processors, wholesalers, retailers, and consumers for many different value-added benefits.

- At a regional scale, the same information used to plan oat-sowing can be used to quantify, schedule, and locate the demand for resources, thus improving supply chain efficiency.
- Towards the end of the growing season, cloud-based crop-yield modeling services could forecast the supply, storage, and logistics requirements for the livestock feed market, potentially matching seasonal net producers with net consumers.
- Data that combines livestock location with locally sensed climate conditions, such as the heat load index, could be shared for public assurance of animal welfare.
- Cattle movement trajectories can indicate animal welfare for the farmer and public alike; spatial animal behavior is known to change with nutritional stress and disease status.[4]
- Livestock location preferences could be combined with pasture biomass characteristics derived from satellite or proximal sensing and correlated with milk or meat quality assessments further along the supply chain.
- Industry-scale analysis of this data could provide insights into nutritional optimization or deficiencies that could be fed back into livestock and pasture management improvements.
- For stud cattle, authoritative breeding quality indicators are commonly Web-available, and the emerging Web of Things opens the opportunity of relating these indicators to commercial herds through automated phenotyping.
- The same opportunities as with cattle would apply to sheep and their wool and meat products; individual wool testing is already undertaken and could be combined with offspring carcase characteristics. Aggregating and analysing such information, correlated with on-farm management practices and breeding records could yield significant industry benefits.

To meet demand due to worldwide population growth, global food production will need to rise by more than 60 percent in the next 40 years.[9] Combined with pressures such as volatile climate conditions and attention to sustainable land use, we need step-change improvements around productivity across the supply chain. A key factor in improving any system's productivity is the ability to reduce costs in the exchange of information or services, as well as improve the quality of information that informs key management decisions.

In Australia, the trends toward aging farmers, a decreasing rural workforce, a need to attract and retain young farmers, a notable growth in farm size, and predicted growth in international commercial opportunities[10] all suggest the need to invest in technologies that assist farmers with situation awareness when they're not in the right place to see for themselves. Further, electronic agriculture has the potential to create virtual service opportunities in agronomy, livestock health, and machinery support, where regionally based consultants provide synchronous identification, analysis, and management advice. Broadband connectivity between rural communities and major cities (in Australia and internationally) will ensure that these farm service providers have access to the computing, data, and technology resources of their city counterparts, but with the advantages of attracting and retaining skilled rural people in their rural lifestyle. Such services could fill the void created by the recent dismantling of the state extension programs that traditionally provided research-founded expertise to farmers.[11]

Farmers' perceptions of electronic agriculture's value to the farm and the quality of the products or services on offer are interdependent. Without farmers who value electronic agriculture, we can't create a viable market around it. Without a viable market, how can we develop a high-quality service and support culture? And, lacking that, how can we facilitate uptake? In the "dependency circle" of electronic agriculture, market demand is inextricably linked to the quality of offered products or services, which in turn influences market demand as well as the level of outside investment in education and infrastructure, all of which feed into the cycle.[12]

We can learn from the wealth of literature on agricultural decision-support systems (DSS). Zvi Hochman and Peter Carberry have found that DSS must be embedded in a support network of farmers, consultants, and researchers; that a critical mass of appropriately skilled people is necessary; and that a DSS should aim to educate farmers' intuition—rather than replace it with optimized recommendations—enabling them to experiment with options that satisfy their needs.[13] Our technology lets farmers specify and experiment with their own events (such as "time to sow") and thus satisfies the latter criterion, but the critical mass and support network criteria rely on the dependency circle.

Angele Giuliano and Johan Bengtsson[14] survey small to medium enterprises (SMEs) internationally to understand the drivers for adoption of Web of Things technologies. Both family farms and industry service providers fall within the scope of the SMEs that benefit. As their survey observes, "there is untapped innovation potential for adding value to products through associated services." The ability to respond reactively is identified, as is the value of offline analysis of sensor data. Our smart farm is well positioned to exploit the innovation potential. In particular, linked data enables Web users to build bidirectional connections among online data, and the data itself can be a critical enabler for infrastructure in business and government.[15] With innovations come economic opportunities:

> *"There is also significant economic potential ... which can be used by businesses as an input to improve the already existing and create additional value services. ... Today, it seems that we are about to approach the triggering point of a virtuous cycle for better services and more involved consumers in the Web economy."*[15]

Agtrix, a software vendor in the sugar cane industry, is an exemplar within a closed data environment. On-farm crop management data is shared with agronomy advisors, logistics providers, harvest contractors, the mills, and government for industry-wide optimization and compliance monitoring. Mills can use the information to predict crop yield; in so doing, they have improved fleet capacity by 30 percent while reducing inefficient processing delays.

Barriers and Drivers

In assessing the business potential for the Web of Things in the agricultural sector, we must consider both drivers and barriers to adoption. These factors will determine the speed and success of new service models and productivity benefits. Some of the existing barriers to adoption are being addressed through wider technology and industry developments, including the following.

- **Level and quality of connectivity.** Rural areas are increasingly connected to a variety of telecommunications systems, including 3G and 4G mobile services and fixed broadband data services provided through a combination of fibre, terrestrial wireless, and satellite coverage. In Australia, the national broadband infrastructure project will connect farm residences with an expected capacity of 25 Mbps download and 5 Mbps upload.
- **Cost of sensors and sensor networks.** Sensor technology is becoming increasingly commoditized, driven by the increasing demand for a wide range of industrial, research, and domestic applications. This will drive down the cost of sensors.
- **Availability of cloud services.** Led by the larger Internet companies, cloud technology has become available at a low cost for software developers to build services in an agile and rapid manner. For the farmer, having data captured, processed, and analyzed remotely through cloud services makes it viable to install and use Web of Things infrastructure and services.
- **Public awareness and fit-for-purpose apps.** With increasing use of smart phones and tablets, there's strong public awareness and use of apps that have been designed to be fit-for-purpose for specific functions. Australian farmers have a high level of mobile phone adoption (85 percent).[3]
- **Data and sensor standards.** The development and widespread adoption of standards for data management and exchange have made it easier to develop reusable and extensible software platforms for Web of Things services, as has been exploited in

the SPARQL query here. Our work relies on the widely used SSN ontology,[7] and a livestock data interchange standard community group was established in the W3C in 2013.

- **Open data policies and practices.** There has been a strong push for government agencies to make their data available for reuse through open licensing frameworks—especially agencies responsible for environmental and natural resources data relevant to agricultural decision support. However, several barriers remain that impede the adoption of new Web of Things services for the agricultural sector. These factors require further research and development involving collaborations among researchers, farmers, software and service businesses, and other businesses in the supply chain through to customers.
- **User acceptance.** DSS must be designed to support and extend farmers' capabilities rather than replace them, as well as to be adoptable by a support network of service providers and other business in the support network and supply-chain connected to agriculture. Our work directly addresses this need.
- **Maturity of software and services industry for agricultural applications.** A recent survey of agriculture software suppliers in Australia highlighted the large number of small-scale software companies, most of which lack the scale, scope, and maturity of business operations to drive more rapid adoption.[16] The developing business models of open data are well suited to this environment.
- **Clear and tangible cost-benefits.** Although there are several high-level estimates of the cost benefits of DSS for Australian agriculture, farmers will require more detailed understanding of costs and benefits specific to their sector. Most cost-benefit analysis has focused on specific sectors, such as cropping, rather than livestock farming, where our work contributes.

Although these barriers are challenging, there are also emerging drivers for adoption of new Web of Things services for the agricultural sector:

- **Integration into vertical supply chains.** One of the success factors in driving adoption appears to be having a key operator in the agriculture supply sector require their producers to use a specific software service to optimize their operations. An example here is sugar cane mill operators requiring growers to use a service like Agtrix to schedule harvesting and milling.
- **Agricultural product and advisory companies move toward digital services.** As exemplified in other industries, many of the larger manufacturers and suppliers of agricultural products are facing reduced margins and are directing their business strategies toward providing services enabled by digital technology. For example, companies such as Syngenta are looking to increase their share of advisory services compared to the supply of fertilizer products,[17] and John Deere hopes to provide advisory services for precision agriculture in addition to farm equipment.[18]
- **Biosecurity and food safety initiatives.** The threat of disease outbreaks has led government and industry regulators to introduce widespread tagging and tracking systems for livestock. The implementation of Web of Things services can extend the value and timeliness of information on such threats and outbreaks.
- **Consumer demand for food provenance.** Consumers are increasingly demanding more information about the conditions under which food is produced, and marketing companies are seeking to exploit this interest to create value-added brands. There are also signs of this trend extending to textiles and leather products.
- **Rural communities' increased use of digital services.** There's interest and unmet demand from rural communities for better access to education, health, and other social services, as well as to entertainment and social media communication with friends and peers. Development of these services feeds in positively to the dependency circle for electronic agriculture.

The technology we presented here relies on Semantic Web standards to support both personalized real-time alerts for on-farm situation awareness and for open data publishing. Although several native SPARQL-like stream query solutions are known, using general-purpose stream processing middleware lets us readily offer other non-semantic services without inducing a semantic processing overhead. We're building in a range of statistically enriched sensor streams to provide knowledge—including *livestock breakout*, *time to irrigate*, *weather for gastrointestinal parasite*, *aberrant behaviour pattern*, and *do not fertilize*—and all of these streams can be selected for local conditions. Our research on enriching alerts, once fired, with semantic linked data information contextualized to the alert situation is ongoing.

Our work is the first approach to use ontology representations of knowledge at runtime both to express descriptions of events over streaming measurement data and to publish summaries as linked open data for longer-term analysis. In the first case, the data is interpreted in a very local temporal and spatial context, and the model for interaction aims to extend the farmer's own knowledge; in the second case, the publication of open

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data is intended to drive industry development that might benefit both the farm's productivity and the farming community's social fabric. Our linked data cube on the Web permits industry-scale tracking of "Things," such as livestock, through the variability of experience in weather and feed as measured by sensors.

Australia's national broadband rollout brings the major opportunity to restructure the industry around the Web of Things capability with the potential to solve identified industry challenges. The industry is ripe for the Web of Things, but industry development throughout the dependency circle is required. Next, we need to undertake the challenging task of quantifying industry-scale benefits. Our analysis might scale internationally, as other large agricultural nations look to invest in rural broadband services. ■

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