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# Semantic IoT: Intelligent Water Management for Efficient Urban Outdoor Water Conservation

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**Abstract.** Water depletion is critical in the dry tropics due to drought, increased development and demographic or economic shifts. Although educational initiatives have improved urban indoor water-use, excessive outdoor wastage still occurs because in most urban areas residential users only have a biannual reading of quantity available to make informed or educated decisions on necessary or unnecessary consumption. For example, the average consumer will water lawns during a designated non-restricted time. The amount of water they use is determined arbitrarily (i.e., either by sight or by blocks of time). In many cases, water is wasted due to over saturation, automated sprinklers that cannot sense precipitation, poor placement of sprinkler direction, etc. Outdoor water use efficiency could be maximized if water flow was shut off when an area of lawn has had sufficient water based on a more intelligent monitoring system. This paper describes the development of an intelligent water management and information system that integrates real-time sensed data (soil moisture, etc) and Web-available information to make dynamic decisions on water release for lawns and fruit trees. The initial pilot-prototype combines Semantic Technologies with Internet of Things to decrease urban outdoor water-use and educate residents on best water usage strategies.

**Keywords:** Semantic Technologies, Internet of Things, Water Conservation

## 1 Introduction

The key drivers to develop sustainable urban water management are external factors such as climate change, drought, population growth and consolidation in urban centers [1, 2]. As the era of cheap water fades, these drivers have increased the need for water industry providers to implement more sustainable strategies in urban water management and conservation. Consumer education on household water use is a strategy used to decrease excessive water consumption [3].

The current focus has been on improving water use inside the home but a large part of the problem exists in outdoor use of water and unintelligent watering systems. The methods to motivate the public to change bad water use habits are driven primarily by mandated water restrictions and initiatives to install water efficient devices (e.g., shower heads). However, to change behaviour, awareness and deeper understanding of the underlying variables, such as soil saturation, soil type, timing and quantity, must be part of the education process [1, 3]. However, to make informed decisions or to automate water consumption processes in smarter ways, one source of data to gauge home use - the water metre - is not adequate. To be successful, a conservation program must get the data to the consumer and make the change financially beneficial to them [3]. People must be given the "geo-temporal" and fiscal context of their consumption:

• How much water do I use or should I use, how much money can I save?

• How do I fare compared to my street, my neighbourhood, my city?

• Based on weather data and evapotranspiration calculations – how much should I have used outside? [3]

*Intelligent water metreing* (IWM) can transform urban water management and determine, in real-time or near real-time, water consumption to provide local or remote data on water consumption [4]. There are municipal initiatives to install smart water metres across wider communities (e.g., Townsville, Mackay and Gold Coast in Queensland) that logs a resident's water usage hourly and streams the data via wireless technologies to a main server, which can be accessed by the home owner via a Web browser to visualize daily water-use. These initiatives are building awareness of water consumption at the user level and alerts to leaks and wastage. However, the data only shows the quantity of water consumed and not whether the water was unnecessarily used in the first place.

The promotion of smarter urban water use will require more extensive data than that currently available to household residents (i.e., total quantity in a 6-month period). For example, the average consumer will water lawns during the designated non-restricted times. The amount of water they use is determined arbitrarily (i.e., either by sight or by blocks of time). In many cases, water is wasted due to over saturation, automated sprinklers that cannot sense precipitation, poor placement of sprinkler direction, etc. If that consumer were alerted or the water flow stopped when an area of lawn has had sufficient water based on a more intelligent monitoring system, outdoor water use efficiency could be maximized. There has been much work in creating smarter homes via internal Internet of Things (IoT) sensor networks for efficient power consumption

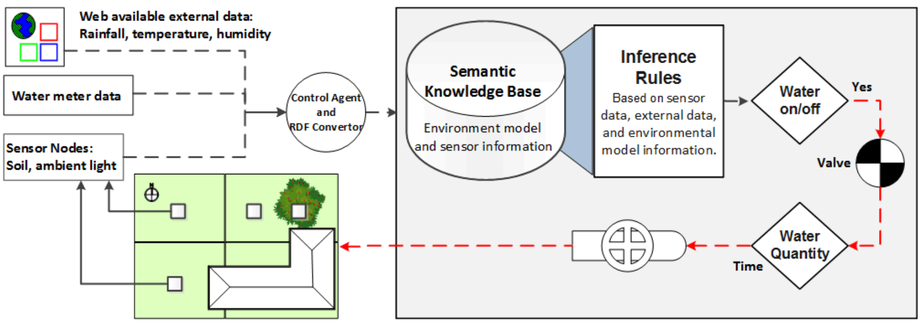


**Fig. 1**. – Architecture for pilot semantically enabled urban irrigation

[5-7]. Semantic technologies (i.e., linked data) combined with IoT could also be applied to better manage water usage in the garden.

The Lawnbot pilot study aimed to advance efficient autonomous irrigation by developing an intelligent system of aggregated data to make decisions on necessary versus unnecessary water use in outdoor watering systems (i.e., water is only used when it is required). The Lawnbot project entails a pilot irrigation management system that makes intelligent decisions on water release based on data from various in situ sensors integrated with external Web available data and information (Fig. 1). Specifically, the research objectives of this project are to 1) infer alerts and trigger autonomous decisions in residential outdoor irrigation systems to minimize waste, 2) maximize plant and fruit growth and 3) build consumer awareness for better water use habits.

## 2 Background

### 2.1 Current Watering Paradigms

North Queensland has been under water restrictions since 1987 following a prolonged dry season and recently in heavy water restrictions since 2015. In Townsville, these restrictions limit watering lawns and gardens up to a maximum of four hours per week per household and in accordance to a strict schedule. In response, local municipal authorities have encouraged residences to adopt plant species with lower water requirements and less wasteful watering behaviours [4].

The Townsville Municipal Council introduced a recommended weekly lawn watering volume of 25mm . By this recommendation, a small lawn in North Queensland of 150 square metres should receive approximately 3750 litres per week to promote healthy growth. Common sprinklers use up to 2100 litres per hour and low-flow sprinklers use under 600 litres per hour [8]. The water pressure would determine how long a sprinkler would take to reach this desired litre capacity. Notably, in a majority of this city, an amount of 3750 litres would be reached in approximately two hours using a common sprinkler. However, residents have been observed to take advantage of the four hours of weekly watering time by running sprinklers for the entire duration. With a single, typical sprinkler, this undesired behaviour can result in a weekly water consumption of 4800 – 8640 litres, which is in excess of what is actually needed by most lawns.

### 2.2 Factors that Influence Required Water Volume

The watering recommendation given by the Townsville Municipal Council represent a general estimate of lawn watering requirements. However, the actual amount of water required for grass depends on many factors, some include: species, sunshine, humidity, evapotranspiration, ground soil moisture, rainfall, etc [9]. Information on these factors can come from three various sources: the sensed environment, inferred from external sources, or from user input.

Real-time information about the surrounding environment, collected by sensors or regular surveillance, is useful for finding the current conditions of the plants and surrounding soil. The current conditions can be employed and tracked mostly to determine if it is an appropriate time to water, as well as the actual amount of water that has been supplied, and how much is needed. For example, the best times to water plants are during cool and humid periods to minimize the amount of water lost to evaporation [10]. Therefore, ambient temperature and relative humidity sensors would be used to determine the best watering times. Further, soil moisture sensors can determine the saturation level of the soil to ensure the soil is not over-watered, which can lead to nutrient depletion in soil and root death from oxygen starvation [11]. Ambient light levels can assist in tracking shade and cloud cover and predicting weather events.

Plants in loose or granular soils tend to drain quickly, which means that plants must be watered for longer, as they only have a short amount of time to take in water. Conversely, cohesive soils such as clay have poor drainage, which gives more time to take in water, but put roots at higher risk of waterlogging if water is supplied too quickly. Vertical soil sensors can monitor and track how water moves through the soil to determine its drainage rate.

Environmental conditions beyond the immediate watering area/s can be inferred using external information. One of the most impactful factors that affects the required watering volume is the weather, especially rainfall, which can eliminate the need for watering entirely. A purely-sensed control system would be able to detect rainfall to halt watering, but would unable to anticipate rainfall. This lack of awareness could lead to wasted water by not taking advantage of natural resources and may put the soil at risk of waterlogging. However, this scenario can be avoided by aggregating weather forecasts, localized sensing equipment, and nearby monitoring stations to track rainfall and predict where and when rain will occur, then adjusting the watering schedule accordingly to leverage natural watering. Similarly, the physical and chemical makeup of the soil can be inferred from real-time sensor information and geographical surveys, given the approximate location of the residence [12].

Another factor that affects the water requirements of plants is evapotranspiration, which is the combined water loss through evaporation and transpiration. Evapotranspiration is specific to plant species, the surrounding environment and represents the optimum amount of water that the plant should receive for healthy growth. Calculating evapotranspiration is a complex procedure that must take multiple factors into account such as ambient temperature, relative humidity, and solar radiation [9]. However, this value, along with drainage rate of the soil and rainfall volume, informs how much water must be supplied through irrigation to meet the needs of the plants in the watering quadrant [13].

### 2.3 Resident specific Information

Some information that affects watering volume that a garden or lawn requires cannot be easily inferred or detected and must be supplied by the user. The three user-defined factors in this study were the species of plants in the watering area, the size and location of the quadrant and the sprinkler type used for watering.

Different species of grass have different water requirements for healthy growth and can enter dormant stages during frigid or drought conditions and can enter dormant stages where they are more susceptible to over-watering. The exact location, size, and shape of the watering area can be used to infer the amount of shade cast on the watering quadrant at different points during the day, which can affect the times when watering is appropriate.

The sprinkler type, such as common, low-flow sprinklers or misters, also has an impact on selecting the best time to water plants and lawns. Airborne watering systems, such as sprayers and misters, deliver water to the entire plants including its stem and leaves. These sprinkler types are better suited to watering in the morning as leaves are susceptible to fungal infection if they are watered at a time when they are not able to dry [8].

### 2.4 Related Work

Recently developed automated irrigation systems emphasize "do-it-yourself", low-cost, and web accessibility enabled by platforms such as Arduino and Raspberry Pi. For example, Vinduino [14] uses multiple moisture sensors at different depths to determine when to water, and prevent overwatering, in vineyards. The developers of the Vinduino project claim 25% water savings across their vineyards [14]. OpenSprinkler provides smart watering control based on historic, current, and forecast weather data [15]. Neither of these projects incorporate Semantic Technologies to introduce a range of data that could enrich the outcomes of the knowledge base.

There are related work that does incorporate semantic technologies such as AGROVOC [16], Agri-IoT [17], CSIRO's Kirby Farm project [18] and the ThinkHome smart home system [6]. AGROVOC is a formal vocabulary in RDF form that allows for the linking of agricultural data. AGROVOC has evolved into a SKOS-XL linked dataset that includes hierarchies of agricultural concepts such as *organisms*, *methods*, *events*, and *processes* and links to other vocabularies about fisheries, environment, and biotechnology [16]. As such, the Agrontology is a potential resource to integrate within the Lawnbot ontology. The ThinkHome project is "smart-home" initiative that incorporates semantic technologies with IoT for improved resource management. However, the focus is predominantly on energy consumption and power management as opposed to water conservation. The Agri-IoT project and CSIRO's Kirby Farm project are semantic web and IoT-based frameworks that are capable of processing multiple data streams for more effective agricultural management [17, 18]. These projects incorporates linked data from multiple data points, including sensed, government and environmental web-based data, for informed and accurate event detection and decision making by farmers. The Agri-IoT and the Kirby Farm projects differ to this study because the focus is in the wider agricultural field rather than the smaller domain of urban lawn management.

## 3 Semantic Knowledge Base and Control Agent

Semantic technology data models aim to capture the meaning of data to represent real world situations for data integration and manipulation [19, 20]. Formal logical paradigms are applied to automate classifications of concepts and the inference of new information. The computer can make intelligent decisions based on conclusions derived through predicate and propositional logic systems embedded in explicit ontological definitions [19, 20].

The Lawnbot ontology (Appendix A) is built on top of the *Semantic Sensor Network* (SSN) ontology [21, 22]. The SSN ontology includes concepts for sensing the environment and making changes through logic-controlled actuators. That is, *Sensors* make *Observations* of *ObservedProperties* belonging to *FeaturesOfInterest* and *Actuators* cause *Actuations* that modify *ActuableProperties* of *FeaturesOfInterest*. For example, the *Observations* of specific areas would infer the *WaterValveActuator* would open the valve to release water.

The *FeaturesOfInterest* relevant to intelligent water management are *Yards*, *Quadrants*, and *WeatherAreas*. That is, each *Yard* consists of several *Quadrants* (Fig. 2) and would fall within a wider *WeatherArea*. Each *Yard* may have distinct watering requirements depending on its properties, for example: different *SoilComposition*, different *MicroClimateFactors* based on the timing and amount of shading, etc.

*Quadrants* contain *Plants*, each of which has a *PlantSpecies*. The dimensions and life cycle status of plants are data-type properties for use in the inference rules to model size and possible impact on shade. *PlantSpecies* determines the crop coefficient, which combined with the dimensions and life cycle status, can together help infer evapotranspiration and determine the watering requirements for the *Quadrant*.

Local sensors gather data at the *Yard* and *Quadrant* levels. At the *Yard* level, sensors measure the *ObservedProperties* that include temperature (ambient and soil), humidity (ambient and soil) and illuminance. At the *Quadrant* level, soil moisture (both

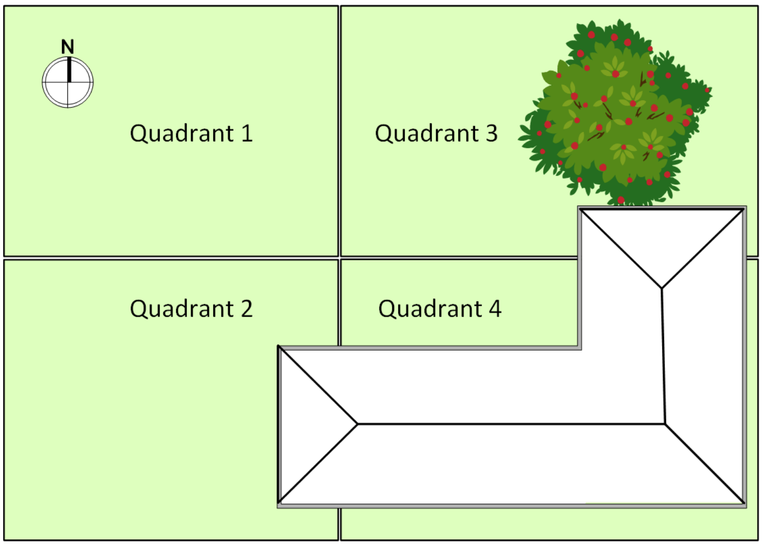


**Fig. 2.** Lawnbot test layout showing individual watering quadrants

superficial and deep) is observed. The sensed data is collected via the control agent and converted to RDF form and ingested to the knowledge base.

Each *Quadrant* contains a *Plant* of a *PlantSpecies*, which determines *WateringRequirements*. *Quadrant* has *SoilComposition*, with properties that can affect watering or fertilization. We further model *Quadrant* size and shading information. *PlantSpecies* has a crop coefficient for determining evapotranspiration. *Quadrant* has a *MicroClimateFactor* affected by shading to determine evapotranspiration.

A *Sprinkler* in each *Quadrant* (or across quadrants) is supplied water by opening a water valve, which is represented as a *WaterValveOnState*. The *SprinklerType* determines the data property *WaterVolumePerMinute*, which is applied in the inference rules to toggle the *WaterValveOnState* for each *Quadrant/s*. Forecast weather data for a *WeatherArea* is modelled by *PredictedProperties* including probability of precipitation, quantity of precipitation, high and low temperature, average windspeed, and average humidity. The concept of *WateringRestrictions* is applied to *Yards* to avoid illegal watering.

The Stardog graph triplestore[1] was used to develop the semantic knowledge base. Stardog was selected as it provides OWL 2 support, SWRL reasoning, and a standard HTTP SPARQL endpoint. For the prototype, climatic data was drawn from CLIMWAT [23], which is an application to share weather data such as rainfall, humidity and temperature, and was used to provide reference data for evapotranspiration calculations. Weather forecasting data is extracted via the Weather

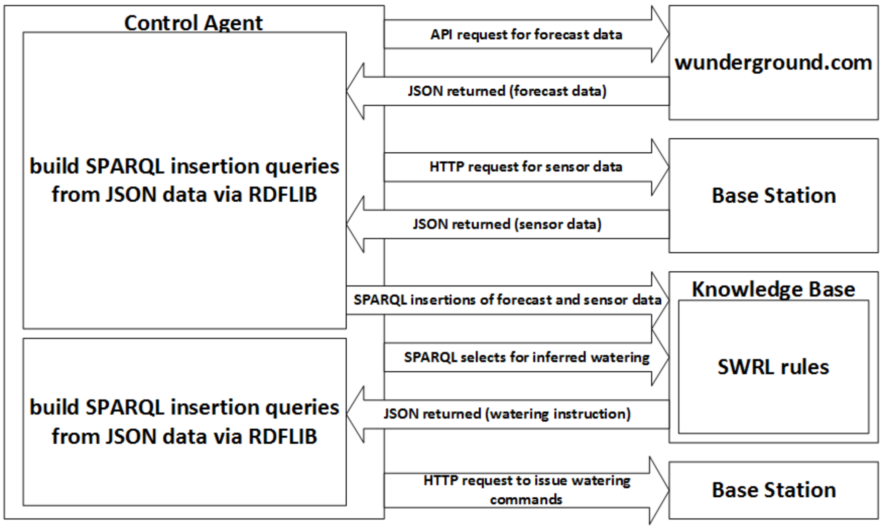


**Fig. 3.** The Control Agent architecture.

[1] http://www.stardog.com/

Underground[2] portal, which combines citizen science data (personal weather stations) with government data (e.g., Bureau of Meteorology) to automate weather predictions. The probability of precipitation, millimetres of forecast rain, high and low temperatures, average humidity and average windspeed were extracted from the forecast data. JSON data for weather forecasts and sensor readings are converted into RDF by the control agent using RDFLib[3] and inserted into the knowledge base via the SPARQL endpoint. For the pilot study, raw sensory and weather was stored in the Stardog triple-store. Custom Python scripts with RDFLib are applied to create SPARQL queries that map the raw data to ontological instances.

The control agent continually polls the base station for sensor data using the requests module for Python and sends it to database (Fig. 3). Each night, the control agent calculates the net water gain or loss for each plant based on watering, precipitation, and evapotranspiration. The Weather Underground portal is also polled for updated forecasts, which means the expected evapotranspiration can be calculated, and so expected gains or losses in water in the coming days can be determined.

Based on the needs of the plants and lawn, the forecast evapotranspiration and precipitation, and watering restrictions, the system can infer whether to turn the water on and for how long (i.e., how many litres of water is required for each quadrant) (Fig. 4). For example, grass on a given quadrant may require 25mm of water per week under typical conditions in summer due to proximity of a shading object such as a house or tree. If six dry days have passed, but a 90% chance of 40mm of precipitation is predicted in the next three days, the system will determine that it should not water the quadrant, but instead wait for the expected rain. The soil moisture sensors will determine if the expected rain has occurred to ground truth the inference outcome.

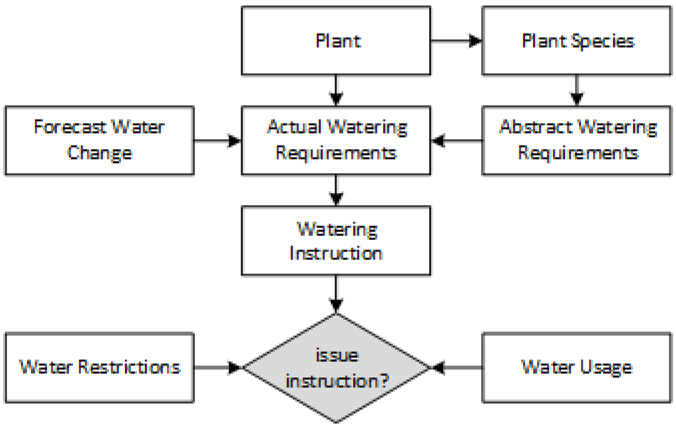


**Fig. 4.** The inference rule schema.

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[2] https://www.wunderground.com/
[3] https://github.com/RDFLib

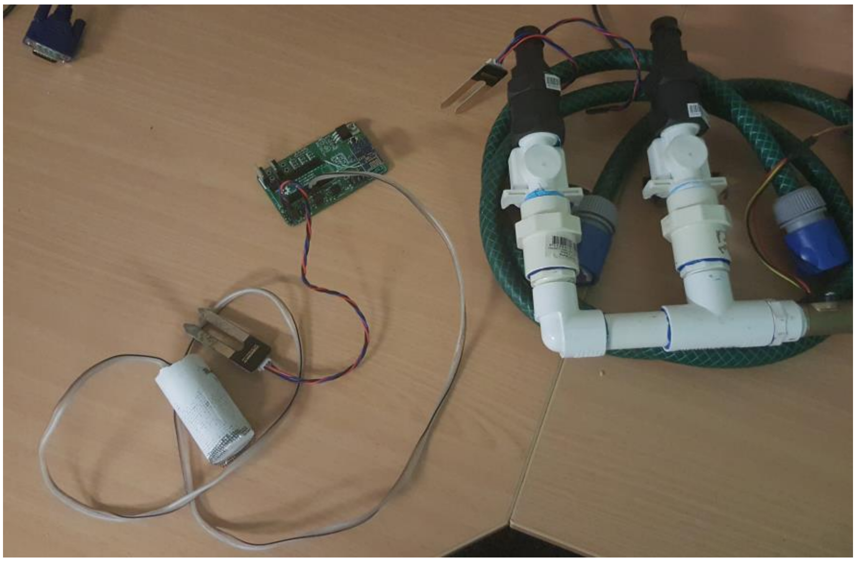


**Fig. 5.** Lawnbot hardware system showing soil sensors and water control system.

## 4 Hardware Implementation

Lawnbot is a prototype sensor and control platform for residential water management (Fig 5). The platform is installed in an outdoor environment, where it uses multiple sensors to gather information on the soil conditions to help optimise the water consumption. The localised weather conditions such as ambient temperature, relative humidity and ambient light levels to ascertain the localised weather conditions such as rain or overcast skies are determined from the environmental sensors installed in each yard. The platform is also capable of interfacing with watering systems to switch the water supply on and off, based on the outcome of the Lawnbot ontology inference rules, and to precisely monitor water usage during watering times.

Two sensor types measure soil saturation at two different depths: a surface-level soil-moisture probe, and a buried gypsum hygrometre. The soil-moisture probe is a device that sits in the topsoil and measures the saturation of the superficial layer of the soil, which is useful for detecting precipitation or when water is otherwise pooling on the ground. The gypsum hygrometre is buried deeper in the soil to monitor moisture levels at root level and is used in conjunction with the soil-moisture probe to track the rate that water moves through the soil during differing environmental conditions, surrounding different plant species, and soil types. Multiple pairs of these sensors can effectively split up a lawn or garden into quadrants, which can be monitored and watered individually. This separation of quadrants is particularly advantageous if they have differing circumstances, such as shade, changing soil types and/or proximity to external water sources such as rivers or dams. Similarly, the system uses multiple valves and flow metres to track how much water is supplied to each watering quadrant (Fig. 2).

The platform can run in a standalone configuration, but its limited awareness of the surrounding area reduces its potential effectiveness. For example, the system may waste water by watering before a rainstorm. By incorporating linked data, the control agent transmits the sensor data to the semantic knowledge base for combination with external data sources such as local weather information to take advantage of natural rainfall and conditions for better water efficiency. In this configuration, no standalone switching occurs and all water management is handled by commands received from the semantic knowledge base.

## 5 Implementation and Discussion

Lawnbot was trialed on a residential property using four watering quadrants (Fig. 2). All four quadrants were spatially separated by the reach of the sprinkler type to avoid water spilling in from other quadrants, but were subject to the same weather conditions. Soil and grass types were consistent for all quadrants, but two quadrants received shade for most of the afternoon, while the other two were in full sun for most of the day.

For direct comparison between Lawnbot and conventional watering schemes, one shaded and one non-shaded watering quadrant were managed by the Lawnbot system, while the remaining areas were watered by typical water usage under locally-imposed timed water restrictions. These restrictions limited watering to only three days per week and for limited times during the morning or afternoon. Water metre readings before and after each hand watering period were used to calculate the total volume used during each session.

Lawnbot watering was enabled throughout the week drawing data from local and external sources to infer water use. Both the soil probe and gypsum hygrometre were installed at the center of each watering quadrant managed by Lawnbot, with hygrometres buried at a depth of 0.5 metres. After a testing period of 30 days, the water usage of each of the quadrants were compared, as well as a visual check of the grass in each quadrant to observe if the grass appeared healthy. On a daily average, the Lawnbot system used less water than the manual system because it stopped the water flow after an inferred period while the manual watering occurred for the full four-hour council allotment.

The outcome is an anticipated decrease in the quantity of water used in outdoor irrigation at the residential level. Table 1 shows a six month simulation over the 2016 January to June period in Townsville and Cairns, which contrasts a dry tropical zone to a wet tropical zone. The control yards are watered 25mm every 7 days on schedule regardless of actual rain. The lawnbot yards are watered so as to maintain 25mm over 7 days while calculating past rain and predicted rain up to three days out. Cairns shows 32% water savings and Townsville shows 21%. Notably, a real-time long term trial is not possible at present due to drought level watering restrictions.

**Table 1.** Simulated inference in Townsville and Cairns, North Queensland

| Month | Predicted average | Cairns Rain | Cairns control quadrant | Cairns lawnbot qaudrant | Townsville rain | Townsville control quadrant | Townsville lawnbot qaudrant |
|---|---|---|---|---|---|---|---|
| Jan | 10.35 | 4.66 | 3.57 | 2.46 | 1.83 | 3.57 | 2.25 |
| Feb | 9.11 | 3.20 | 3.57 | 2.29 | 2.23 | 3.57 | 1.96 |
| Mar | 6.29 | 5.50 | 3.23 | 2.29 | 8.84 | 3.23 | 2.29 |
| April | 8.58 | 3.11 | 4.17 | 1.57 | 0.22 | 4.17 | 3.23 |
| May | 7.53 | 2.73 | 3.23 | 2.81 | 0.02 | 3.23 | 3.42 |
| June | 6.26 | 1.21 | 3.33 | 2.97 | 0.52 | 3.33 | 3.40 |
| Total | | 20.41 | 21.09 | 14.38 | 13.66 | 21.09 | 16.56 |

The immediate benefits of the system are to the council's water management program, residents who pay for water and/or users who are concerned with water depletion. The proposed output will be a pilot system that will be demonstrated by automatically managing residential outdoor irrigation for lawns and fruit trees based on various disparate data input sources and a semantic system that “understands” how the variables interact.

Automating the release of water (the system manipulates the valve) will further benefit the resident and promote use of the system. The residents will visually see when water should or should not be used and money saved based on the aggregate of available data and inferred output, which are relevant to changing water consumption behaviour [3].

## 6 Conclusions

This paper presented the prototype Lawnbot water management platform, which is an automated watering system for residential lawns and gardens that applies Semantic and IoT technologies. The resulting system incorporates real-time sensor data, weather forecasts, geological and environmental information to infer the precise amount of water needed to minimize water wastage without compromising the health and wellbeing of the lawn or garden. The prototype combines a sensor-actuator system that automatically manages the water flow in yards based on semantic inference. The combination of data from multiple sources with a sensor-actuator system has the potential to make better watering decisions than other systems of its kind. A method to evaluate the system was discussed that compared the watering performance of the semantic-controlled platform to manual watering under council water restriction guidelines.

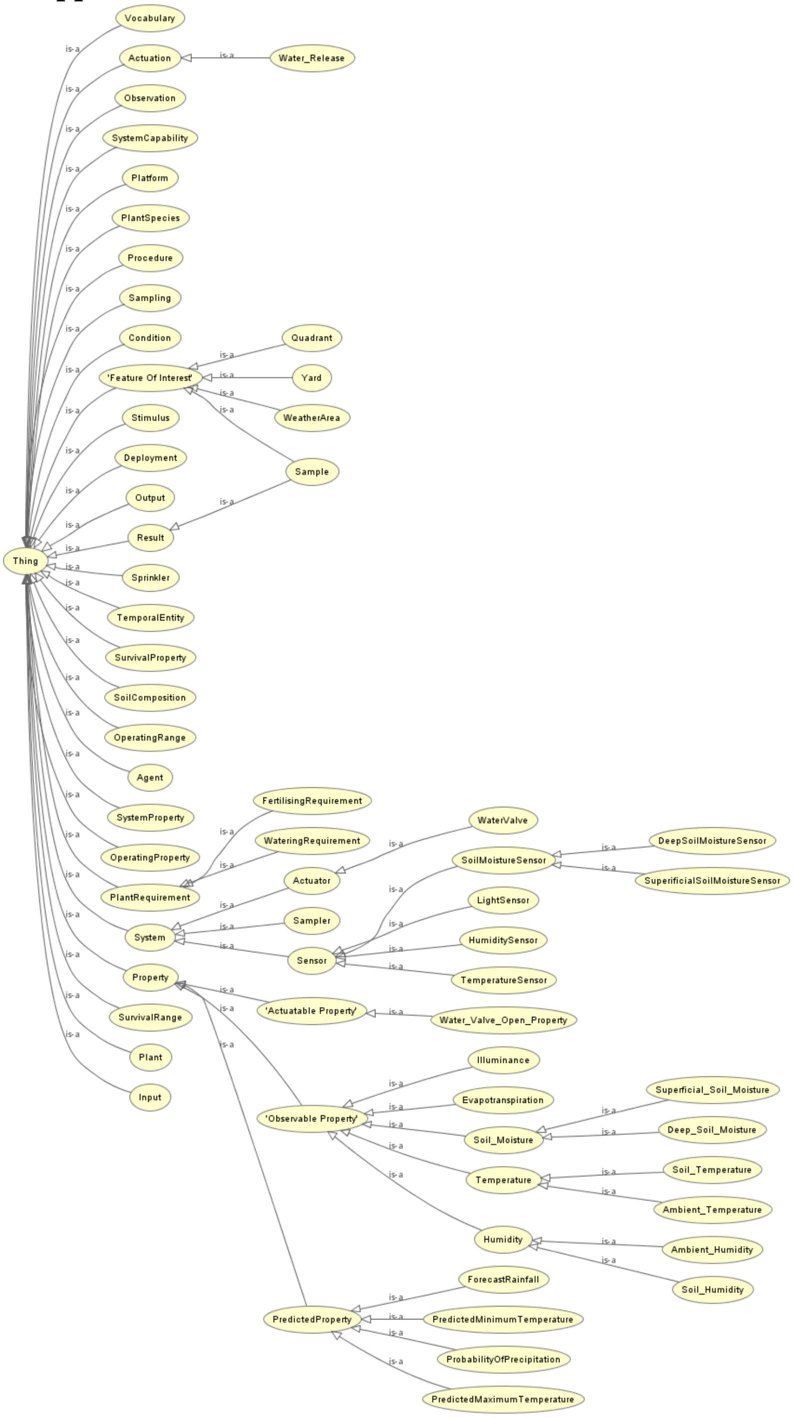
Future work of the Lawnbot semantic knowledge base includes the refinement of the Lawnbot ontology, a user dashboard and extending controls to fertilisers. The spatial accuracy of weather predictions and rainfall tracking can also be augmented by gathering information from nearby urban sensor installations, and from other IoT platforms. A visualisation tool such as a user dashboard would better inform users of their water usage habits and compare with nearby properties. The residents will visually see when water should or should not be used and money saved based on the aggregate of available data and inferred output. Users will also be able to define their own watering quadrants with specific shade areas and plants to input into the knowledge base. Further, there are plans to expand the system to manage controls of liquid fertilisers and pH balancing for improved plant health.

## References


1. Boyle, T., Giurco, D., Mukheibir, P., Liu, A., Moy, C., White, S., and Stewart, R.: 'Intelligent Metering for Urban Water: A Review', Water, 5, (3), pp. 1052-1081 (2013)
2. Hussey, K., and Dovers, S.: 'Managing Water for Australia: the social and institutional challenges'.CSIRO Publishing (2007)
3. Hill, T., and Symmonds, G.: 'Sustained water conservation by combining incentives, data and rates to effect consumer behavioural change', Water and Society, 153, (1), pp. 409 (2012)
4. Manning, C., Hargroves, K., Walker, M., Lange, J., Igloi, S., Bruce, G., and Desha, C.: 'Dry tropics water smart: a community based approach to residential outdoor water consumption'. In 2013 Australian Water Association Conferenc (OzWater 2013), Perth, WA (2013)
5. Wilson, C., Hargreaves, T., and Hauxwell-Baldwin, R.: 'Smart homes and their users: a systematic analysis and key challenges', Personal and Ubiquitous Computing, 19, (2), pp. 463-476 (2015)
6. Reinisch, C., Kofler, M.J., and Kastner, W.: 'ThinkHome: A smart home as digital ecosystem'. In 4th IEEE International Conference on Digital Ecosystems and Technologies (DEST), pp. 256-261, Dubai, United Arab Emirates (2010)
7. Cook, M., Myers, T., and Trevathan, J.: 'A Prototype Home-Based Environmental Monitoring System', International Journal of Smart Home, 7, (6), pp. 389-404 (2013)
8. How to Save Water at Home, https://www.townsville.qld.gov.au/water-waste-and-environment/water-supply-and-dams/saving-and-consumption, last accessed February, 2017
9. Allen, R.G., Pereira, L.S., Raes, D., and Smith, M.: 'Crop evapotranspiration - Guidelines for computing crop water requirements'.Food and Agriculture Organization of the United Nations, Rome (1998)
10. Smajstrla, A.G., and Zazueta, F.: 'Evaporation loss during sprinkler irrigation'.University of Florida Cooperative Extension Service, Institute of Food and Agriculture Sciences, EDIS (1994)
11. Water-logging, http://soilquality.org.au/factsheets/waterlogging last accessed January, 2017
12. Soils series, https://data.qld.gov.au/dataset/soils-series, last accessed January, 2017
13. Nouri, H., Beecham, S., Kazemi, F., and Hassanli, A.M.: 'A review of ET measurement techniques for estimating the water requirements of urban landscape vegetation', Urban Water Journal, 10, (4), pp. 247-259 (2013)
14. Vinduino, a wine grower's water saving project, https://hackaday.io/project/6444-vinduino-a-wine-growers-water-saving-project, last accessed June, 2017
15. OpenSprinkler, https://opensprinkler.com, last accessed 2017/07/06, 2017
16. Caracciolo, C., Stellato, A., Morshed, A., Johannsen, G., Rajbhandari, S., Jaques, Y., and Keizer, J.: 'The AGROVOC linked dataset', Semantic Web, 4, (3), pp. 341-348 (2013)

17. Kamilaris, A., Gao, F., Prenafeta-Boldu, F.X., and Ali, M.I.: 'Agri-IoT: A semantic framework for Internet of Things-enabled smart farming applications'. In IEEE 3rd World Forum on Internet of Things (WF-IoT), pp. 442-447, Reston, USA (2016)
18. Taylor, K., Griffith, C., Lefort, L., Gaire, R., Compton, M., Wark, T., Lamb, D., Falzon, G., and Trotter, M.: 'Farming the Web of Things', IEEE Intelligent Systems, 28, (6), pp. 12-19 (2013)
19. Allemang, D., and Hendler, J.: 'Semantic Web for the working ontologist, 2nd Edition: effective modeling in RDFS and OWL'.Morgan Kaufmann, Burlington, MA, USA (2011)
20. Myers, T., and Atkinson, I.: 'Eco-informatics modelling via semantic inference', Information Systems, 38, (001), pp. 16–32 (2013)
21. Semantic Sensor Network Ontology, https://www.w3.org/TR/vocab-ssn/, last accessed 2017/07/04, 2017
22. Compton, M., Barnaghi, P., Bermudez, L., García-Castro, R., Corcho, O., Cox, S., Graybeal, J., Hauswirth, M., Henson, C., Herzog, A., Huang, V., Janowicz, K., Kelsey, W.D., Le Phuoc, D., Lefort, L., Leggieri, M., Neuhaus, H., Nikolov, A., Page, K., Passant, A., Sheth, A., and Taylor, K.: 'The SSN ontology of the W3C semantic sensor network incubator group', Web Semantics: Science, Services and Agents on the World Wide Web, 17, pp. 25-32 (2012)
23. CLIMWAT, http://www.fao.org/land-water/databases-and-software/climwat-for-cropwat/en/, last accessed August, 2017

# Appendix A


Thing
Vocabulary
Actuation
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