 doi:10.20944/preprints202010.0429.v1

Article

IRRISENS: An IoT platform based on microservices applied in commercial-scale crops working in a multi-cloud environment

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Abstract: Research has shown the multitude of applications that IoT, cloud computing and forecast technologies present in every sector. In agriculture, one application is the monitoring of factors that influence crop development to assist in making crop management decisions. Research on the application of such technologies in agriculture has been mainly conducted at small experimental sites or under controlled conditions. This research has provided relevant insights and guidelines for the use of different types of sensors, application of a multitude of algorithms to forecast relevant parameters as well as architectural approaches of IoT platforms. However, research on the implementation of IoT platforms at the commercial scale is needed to identify platform requirements to properly function under such conditions. This article evaluates an IoT platform (IRRISENS) based on fully replicable microservices used to sense soil, crop and atmosphere parameters, interact with third party cloud services, planning and scheduling irrigation as well as control of irrigation water control devices. The proposed IoT platform was evaluated during one growing season at four commercial scale farms on two different broadacre irrigated crops with very different water management requirements (rice and cotton). Five main requirements for IoT platforms to be used in agriculture at commercial scale were identified from implementing IRRISENS in rice and cotton production: scalability, flexibility, heterogeneity, robustness to failure and security. The platform addressed all these requirements. The results showed that the microservice approach followed in the platform is robust against both intermittent and critical failures in the field that could occur in any of the monitored sites. Further, processing or storage overload caused for any reason at one farm did not affect the performance of the platform regarding the other monitored farms. This paper also discusses how the microservice approach can address the data heterogeneity issue when crops with different management requirements are monitored. Since there are no shared microservices among farms, the IoT platform proposed here also provides data isolation maintaining data confidentiality for each user, which is relevant in a commercial farm scenario.

Keywords: IoT platform, microservice, smart agriculture, irrigated crops, Agriculture 4.0

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1. Introduction

Irrigated agriculture is a key industry to meet the food requirements of a constantly increasing world population in which any improvement in productivity has direct benefits on society and the environment. In the last decades, the application of computational technologies in agriculture has increased dramatically, resulting in increased productivity and more efficient use of natural resources. Since irrigation is needed in semiarid areas where precipitation is low to meet plant water requirements, the use of water-saving technologies in these areas, often characterized for having water scarcity issues, may have a beneficial impact on farm management and cost efficiencies, but also on the availability of water resources for other crops or even sectors [1]. As agriculture demands 70% [2] of freshwater in current food production systems, saving and optimizing water resources is

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imperative to achieving the Food and Agriculture Organization (FAO) expectation to double food production by 2050 [3].

The application of information and communication technologies in agriculture is represented by several concepts such as Precision Agriculture (PA) [4] and smart farming [5]. However, as discussed in [6], such concepts have a broad interpretation which makes the use of these terms confusing. In an industrial agriculture scenario, the application of technology considers not only data acquisition and monitoring but also an integration of services and impacts in the business process that it is close to the concept of Industry 4.0 [7]. That is, the development of a system has a maturity chain comprising six levels: computerization, connectivity, visibility, transparency, predictive capability and adaptability [8]. In the work presented here, the application of Internet of Things (IoT), smart sensing [9], big data and services, and its integration is discussed in order to provide elements to farm automation and decision-making following the paradigm of Agriculture 4.0 [10]. In the context of Agriculture 4.0, several IoT platforms have been proposed to monitor, control and forecast crop parameters. Monitoring and control will entail the first three levels of the maturity chain for the development of a system (computerization, connectivity and visibility). Forecasting parameters, on the other hand, would represent the first stages of the fourth level, transparency, considering that forecasting helps to understand the crop scenario and cannot be used to simulate crop scenarios as suggested in the fifth level of the maturity model [8].

1.1. IoT Platforms for agricultural services

Several system architectures (platforms) have been proposed to deal with the challenges presented in agriculture. Some platforms are cloud-centric, where the smart sensing devices installed in the field send data to a remote central processing system that may even support decision making [11], [12], [13], [14]. Other IoT platforms rely on hybrid structures composed of edge or fog computing and cloud computing useful to deal with communication shortcomings between the farm and the cloud [15], [16], [17]. However, interaction with external services such as remote-sensed data providers or weather forecast services is challenging to address through edge and fog computing, and in most platforms, those interactions with external services are performed by the cloud. **Error! Reference source not found.** shows these platforms classified based on two major categories: organization (how the platform is organized in a computation environment) and software architecture, which determines the flexibility and adaptability of a platform. The classification took into consideration the fog computing definition "*as an extension of cloud computing to the edge of the network*" [18]. It implies that the fog has the same basic structure of the cloud but existing in the farm to deal with communication latency among other issues [19,20]. Edge computing is understood as "*as any computing and network resources along the path between data sources and cloud data centres*" [21].

Such platforms may be based on software frameworks such as FIWARE [14,16], [22], proprietary or custom-made software frameworks following a multitude of software architectures [23] or microservices-based architecture [24], [25], [26], [27]. FIWARE makes interoperability between applications called enablers and has the context broker ORION in its core. The context broker is the element to orchestrate communication between all enablers and external services using the NGSI protocol [28] or an IoT agent in case NGSI is not present. One of the concerns about FIWARE is the difficulty to isolate data from different sources while using ORION context broker since it uses only one database to store data from all services and this may compromise data isolation. In [29], the usage of one context broker for each farm has been discussed in the case of a commercial-scale scenario. This, however, implies that it would have several instances of the platform instead of one.

The application of these IoT platforms has been evaluated in experimental sites or under controlled conditions (greenhouses) [30], [31]. Although these studies provide relevant insights and guidelines about architectural approaches for IoT platforms, proper use of sensors, and application of algorithms for forecasting relevant parameters, more research is needed to test IoT platforms that could deal with the actual requirements of commercial farms.

This article presents and evaluates an IoT platform called IRRISENS based on fully replicable microservices used to sense and monitor soil, crop and weather data, forecast relevant parameters,

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interact with external (weather and remote-sensed data providers) and third-party cloud services, and control irrigation control devices (Figure 1). IRRISENS is organized following the concept of a digital crop model, a microservice that collects data from several microservices to compose a set of parameters that represent the monitored crop, and all microservices refer to this model to perform their processing. The proposed IoT platform was evaluated on broadacre irrigated crops (rice and cotton) at four commercial farms where one company provides the smart sensing device communication [32] and a second company provides the irrigation outlets and automation units [33] to control water distribution. Both providers manage their equipment through a cloud service, and they use different field communication technology with its own protocols, data organization and communication APIs to collect data and interact with field equipment.

Table 1 – IoT Platforms in agriculture context

Organization			Software architecture		References
Cloud	Fog	Edge	Monolithic	Microservices	
Application-specific and generic services			Application-specific	Generic services	[14], [11], [22]
Application-specific and generic services	Application-specific		Application-specific	Generic services	[16]
Application-specific and generic services	Application-specific		Generic services	Application-specific	[24], [15]
Application-specific and generic services			Generic services	Application-specific	[34]
All software runs here			Platform and application-specific		[35] [36], [37], [38], [39], [40], [41]
Data processing and specific services		Application-specific	Application-specific		[13]
Application-specific services	Application-specific services	Application-specific			[17]
Application-specific and generic services			Generic services	Application-specific	[23]

The contributions of this paper are threefold. Firstly, we propose a cloud-centric IoT platform composed of microservices and smart sensing devices to meet the commercial-scale agriculture requirements. Secondly, as the platform was evaluated in four farms planted with very different crops in terms of water management, we show how the proposed microservice-based architecture addressed data heterogeneity related issues in smart sensing. Thirdly, we present the robustness of the platform while one of the loggers installed in a monitored crop had failed and flooded the platform with messages. The microservice organization avoided failure in other monitored farms and a comparison with a monolithic service is evaluated.

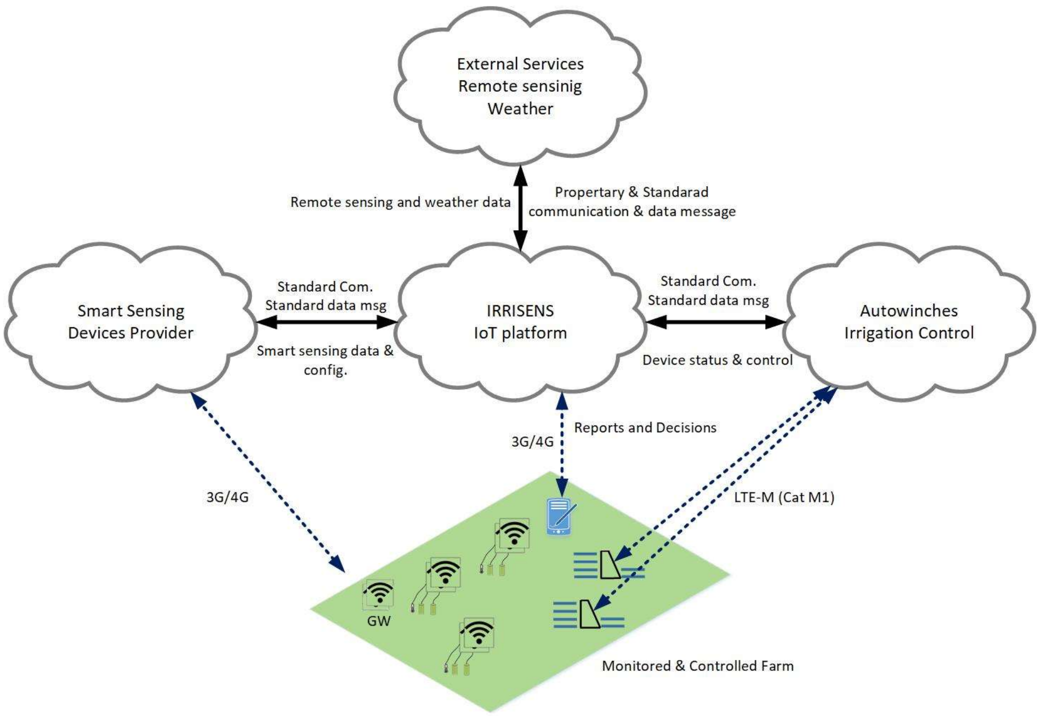

Figure 1 –Schematic diagram of the IoT platform presented in this study (IRRISENS) and its interaction with external services

2. Materials and methods

2.1. The IRRISENS IoT Platform

The IRRISENS platform is cloud-centric and it is composed of two different types of software elements: native cloud services and microservices. A microservice is by definition an independent process that performs a specific task and communicates by means of a lightweight mechanism with minimum centralized management [42,43]. Further, it can be "*deployed, changed, substituted, and scaled independently of each other*" [44], as opposed to monolith software where "*modules cannot be executed independently*" [42]. These elements (native cloud services and microservices) provide domain-specific services all related to the agriculture context and are organized in six modules as depicted in Figure 2. Each module is composed of fully replicable services and microservices that deal with sensing data, monitoring farm status, controlling irrigation and forecasting decision-making features, data management and presentation, as well as integration with external services. The platform interacts with external services running on their own clouds in order to monitor and control IoT devices already installed in the farms, which operate with their own messaging protocol based on both open standards and proprietary communication protocols. Some services are based on a publish/subscribe mechanism and others are based on external APIs using MQTT, JSON or REST.

The services not specifically related to the agriculture domain but essential to the IRRISENS platform, are called General Cloud Services (GCS), and in the cloud, there are controls about their performance and configuration. The GCS present native cloud features such as elasticity, which means the cloud will provide enough resources to execute the service and process data regardless of the data load imposed by the service. The services related directly to agriculture are called Application Specific Services (ASS) and they run according to the resources and features configured by the IRRISENS administration user, which directly affects the IoT platform's performance. The ASS's are microservices specialized for agriculture tasks and thus, must be robust and capable to deal with data heterogeneity, data processing, forecast and device control. In this work, all ASS's ran with the same resource configuration and none of them were configured with elasticity, i.e. each ASS will run with the same amount of configured resources from the cloud platform. All GCS and ASS were configured to run with authentication between them and any other services and microservices. This guarantee data isolation between farms.

The IRRISENS core module is composed of the "crop digital model" and "crop parameter" microservices (Figure 2). All ASS's in the platform refer to the crop digital model to perform its processing. The crop digital model is based on the evapotranspiration model [45,46] and it is specific for each crop. The "crop parameter" microservice is responsible for collecting relevant data from the available sources (soil moisture sensors, weather stations and remote sensing services) to fulfil the model. The "crop digital model" is a fundamental element in the platform since it describes the physical crop under monitoring and control. The model provides not only the parameters to be collected by the sensors, but as is related to a type of crop, it also determines what data means and give support to deal with data heterogeneity.

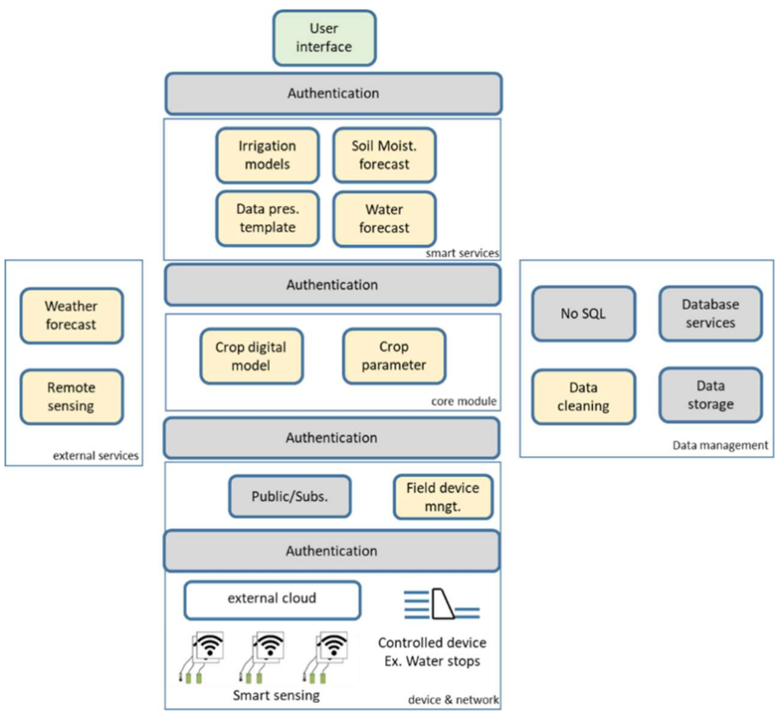

Figure 2. Modules and microservices that compose the IRRISENS IoT platform. Application-specific services (ASS) directly related to agriculture are indicated in yellow colour while general cloud services (GCS) are indicated in grey colour.

The IoT device & network module is composed of services and microservices to interact with smart sensing devices, control devices and external clouds that control other devices in the field that IRRISENS must interact with. In this module, the use of both GCS and ASS is essential to deal with several protocol communication technologies and provide platform scalability and robustness. IRRISENS may use the publish/subscribe services and microservices dedicated to deal with smart sensing devices. The "field-device management" microservice deals with labelling and format of data

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collected from the field before data is processed by the ASS "crop parameter" and stored in the GCS "data storage" microservices.

In the external services module, the ASS microservices are responsible for the exchange and collection of data from external data providers, such as remote sensing platforms and weather services. There is a specific microservice for weather forecast and other for remote sensing. Both microservices are instantiated (i.e. start running the microservice) for each farm following specifications about which data must be collected at each farm. Examples of data specification are GPS coordinates of a farm to receive weather forecast from the nearest weather station available and crop reflectance data obtained from satellites used to compute vegetation indexes such as the normalized difference vegetation index (NDVI). These microservices ("weather forecast" and "remote sensing") deal with data with different spatial and temporal resolutions and organize data according to the storage requirements of IRRISENS. An example of this spatial and temporal data heterogeneity is data from weather stations collected from a specific farm at hourly intervals, data from weather forecast services for large areas collected daily and data from satellite imagery collected at five-day intervals.

The Data Management module has a "database services" and "data storage" microservices that manage data persistency in the platform. All microservices from this module do the basic data processing such as cleaning data from the field and storing data in raw format. In some cases, sensors do not provide a ready-to-use value and raw data collected need to be processed to obtain a meaningful value with a specific unit. That is the case, for instance, of the Watermark sensors (Model 200SS, Irrometer Company inc., California, USA). The sensor measures the resistance value (*ohms*) that needs to be converted to soil water tension (kPa), a measure of the energy required to extract water from the soil. In this case, the platform stores the raw data to evaluate for possible anomalies in the measurement and then one specialized microservice calculates the soil water tension according to the sensor manufacturer's equation.

The Smart Services module is composed of four microservices that run simple or complex algorithms (machine learning algorithms) to process data from the lower modules and compose them to provide services to farmers. That is, for instance, soil moisture forecasts and calculation of crop parameters or models to estimate crop water needs, which are useful for the decision-making process and controlling field equipment such as the irrigation control winches responsible to control water distribution during an irrigation event.

The Integrated service is the module where the interface between final users and the IoT platform is managed. The elements in this module control user authentication, data visualization for monitoring and interfaces to control actuators in the field.

The ASS may be organized and instantiated for each monitored crop and GCS can be securely shared between ASS to make it possible to have a simultaneous set of microservices instances in the same structural element (the cloud) to provide customized behaviours according to instantiation (code into computer memory ready to be executed) of selected microservices. As all microservices must be authenticated by a cloud platform, there is an important level of security that guarantees one microservice instantiated for one farm does not interact with microservices or data from other farms. The microservice architecture also provides better computational resource allocation, since each microservice is an independent service to which the cloud allocates an amount of memory space and processing time.

2.2. Data isolation approach

Commercial farms require robust IoT platforms and data isolation as the collected data in the platform is sensitive for the farm business. Crop and irrigation management are directly related to crop yield and therefore, the platform must provide security mechanisms that avoid possible breaches that could compromise data secrecy.

In IRRISENS, security is based on authentication and security certificate among all elements of the platform, regardless of internal or external services. As illustrated in Figure , every ASS has the credentials to run and access any GCS. Those credentials are created and configured by the administrator. These may be associated with all ASS running for one farm, which creates a chain of authenticated ASS that manipulates one digital crop model.

2.3. Platform Deployment Scenarios

IRRISENS was tested in the 2019/20 summer season in two commercial cotton and two rice farms located in the Murrumbidgee Valley in NSW, Australia. A Wi-Fi network consisting of a cellular data modem connected by ethernet to a Ubiquiti Nanostation M2 directional Wi-Fi access point was installed at each site to provide internet connectivity to the monitored bays (3-4 bays per site; see Figure 4). IoT Wi-Fi-based loggers (WiField, Goanna telemetry, Goondiwindi QLD, Australia) were used in all the sites to collect and send data from the sensors to the platform every hour [32].

Cotton was furrow irrigated by means of a bank-less channel irrigation system. Soil moisture in the cotton farms was monitored at the centre of three contiguous bays with a multi-sensor capacitance probe (EP100G-12, Entelechy Pty Ltd, Golden Grove, SA, Australia) with sensors at 0.10 m intervals along the length of the probe (1.2 m) that collected volumetric water content, temperature and salinity data [47]. Soil water tension (kPa) was also monitored at 0.20 m below the surface by means of a pair of Watermarks (model 6440 Davis Instruments, United States) and a temperature sensor (DS18B20, Maxim Integrated) using a standard equation [48] (see the detail of the sensors in Figure 4). Compared to the capacitance probes, the Watermark sensors do not need calibration for different soils and provide a low cost and simple way for determining when soil is reaching limiting moisture levels that could affect plant physiology. Table 2 summarizes the parameters monitored at the cotton farms.

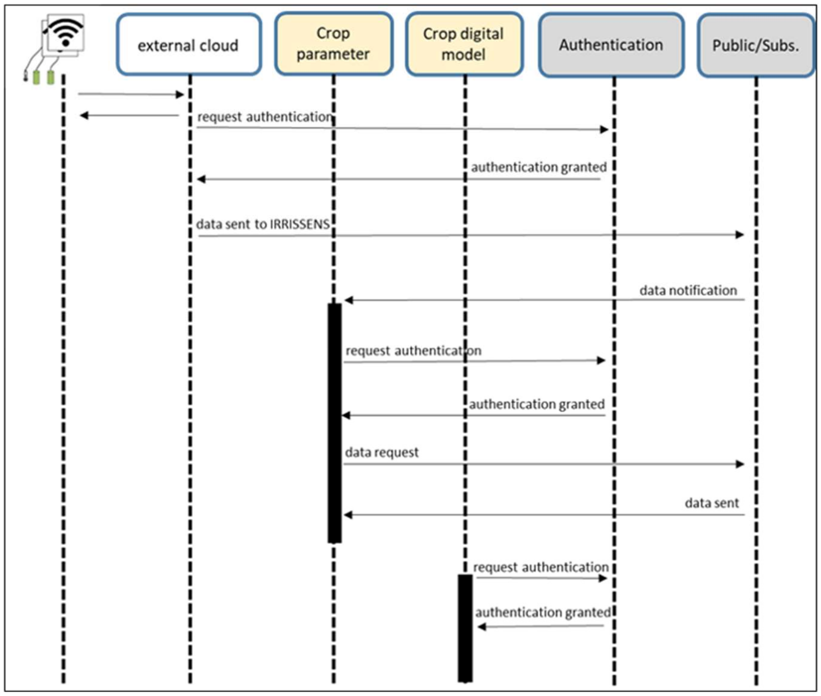

Figure 3 – Mechanisms of authentication among all elements of IRRISENS

Table 2 Details of the farms and parameters monitored at each of them.

Farm	Area (ha)	Interval (min)	Weeks monitored	Parameters Monitored

Cotton 1	2.7	60	24	Soil water tension at 0.20 cm depth Soil temperature at 0.20 cm depth Volumetric water content (%), salinity (dS m-1) and temperature (°C) from 0–1.2 m at 0.10 m intervals
Cotton 2	22.0	60	22	
Rice 1	33.4	60	16	Water height (mm) Soil, water, and air temperature (°C)
Rice 2	10.0	60	14	

Rice was grown at both farms following a delayed permanent water strategy where the crop is not permanently flooded until late tillering. Like in the cotton farms, multi-sensor capacitance probes were installed in 3-4 contiguous bays. In this case, however, soil moisture was not a relevant parameter to monitor because sensors were installed in January when bays had been already flooded. The capacitance probes were used instead of measured water height in the ponded bays according to [49]. Probes were 0.8 m long and were installed to leave the first 0.6 m from the top above the soil surface to be able to monitor water height but also soil, water, and air temperature at the canopy level. This case in which the same probe can be used to measure different parameters (volumetric water content and water height) and only one of them (water height in this case) is relevant for the irrigation management at a specific crop stage is an example of data heterogeneity. Within the IRRISENS platform, the "Crop parameter" microservice deals with this by referencing data collected by the probe as a volume of water in the soil, processing data to determine the water height and requesting the storage of both raw and calculated data in the platform.

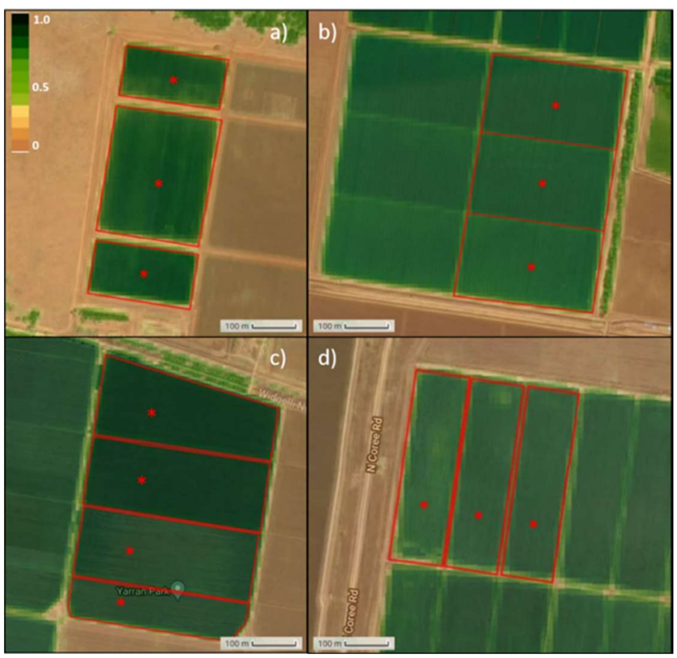

Figure 4. Sentinel-2 NDVI image (obtained from IrriSat [50]) of the cotton (a and b) and rice farms (c and d) with detail of the bays monitored (red polygons) and location of the sensors (red asterisks) at each site.

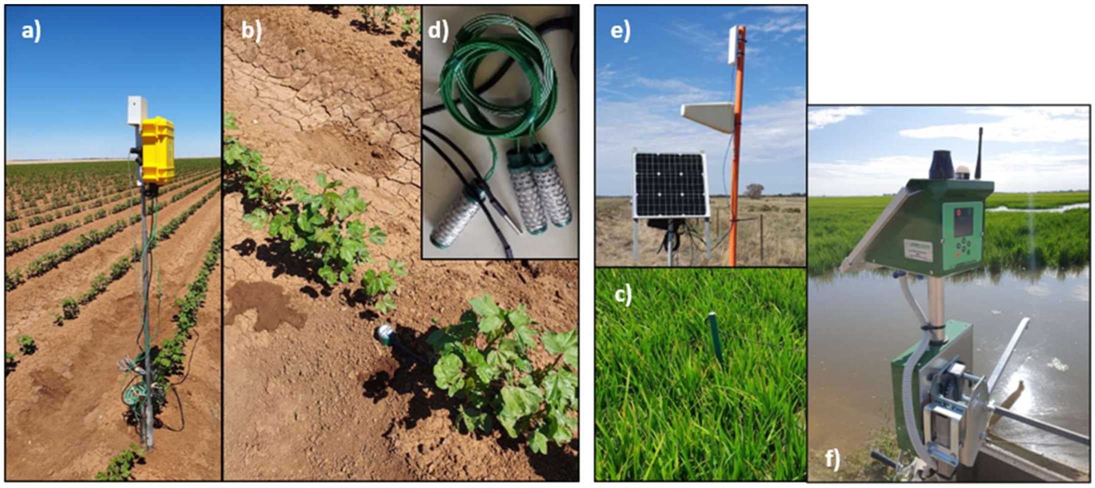

Figure 5 Pictures of a datalogger (a), multi-sensor capacitance probes installed in a cotton and rice farm (b and c), Watermark sensors used (d), a Wi-Fi access point (e) and an IoT irrigation control autowinch.

Figure 6 illustrates a dataflow diagram with an example of the organization of the GCS and ASS services valid for the monitoring of a cotton and rice farm. The microservice "crop parameter" collects all the data coming from the sensors in the field and organize these in a way that can be read by the "crop digital model" microservice. Once the farm and type of crop are identified by the "crop digital model" microservice, all the data is subjected to a data cleaning process ("data cleaning" microservice) where abnormal readings from the sensors are detected and data is made available for the "crop digital model" microservice to process accordingly. The "crop digital model" microservice uses then data from the closest available weather station to calculate the reference evapotranspiration (ETo) according to [45] and remotely sensed NDVI (from Sentinel-2 imagery) to obtain a site-specific crop coefficient (Kc) according to [51] to estimate the crop evapotranspiration (ETc = Kc x ETo). The "soil moisture forecast" microservice in cotton and "volume water forecast" microservice in rice (see Figure 6), use this digital representation to forecast relevant parameters for the irrigation scheduling. Finally, the ASS "data presentation template" organize data in a user-friendly way for the users to consult and evaluate.

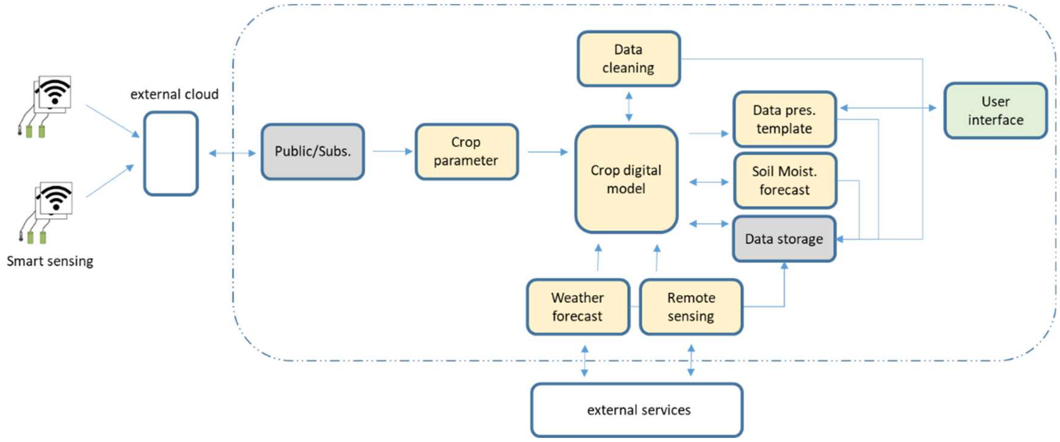

Figure 6. Dataflow diagram with an example of the organization of the General Cloud Services (GCS; grey colour) and Application Specific Services (ASS; yellow colour) within the platform for the monitoring of a cotton or rice farm.

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3. Results

Once sensors were deployed in the field, IRRISENS started collecting data from the set of sensors installed at each farm as well as from external services at the specified time intervals. This information was useful for the farmers/agronomists to make decisions regarding the water management of each crop. Figures 7 and 8 illustrate the type of data generated by the “crop parameter” microservice and how data is made available to the farmer/agronomist.

In cotton, continuous monitoring of soil water tension and seven-day water tension forecasts enabled the agronomists responsible of the farms to schedule irrigation avoiding values above 60 kPa, when cotton plants start showing symptoms of water stress (reference) (Figure 7a). As expected, the remotely sensed NDVI obtained from an external service presented low values early in the growing season when most of the pixels in the satellite image contained bare soil and increased progressively up to ~0.90 when crops reached full ground canopy cover (Figure 7b). Likewise, water requirements (ETc) of crops increased along the growing season as biomass increased.

In rice, despite the probes were the same type as those in the cotton farms, the “crop parameter” microservice was configured to compute water height instead of volumetric water content (Figure 8). Monitoring water height was relevant for the water management in rice farms for two reasons. Rice is sensitive to low temperatures at the microspore stage when temperatures below 17°C can damage the pollen and lead to floret sterility (ref). Since temperature changes in water take longer to occur than in the air, water depths of 0.25 m have been recommended at the microspore stage to protect the crop against low temperatures. Almost real-time data of the water depth in flooded bays provided the information needed by farmers to decide whether to open the inlets to raise the water level when low temperatures were envisaged. This measure (water depth) along with information about each bays' dimensions enabled the platform to estimate the amount of water needed to refill the water losses by water evaporation and transpiration of plants (ET_c) to maintain the desired water depth within each bay.

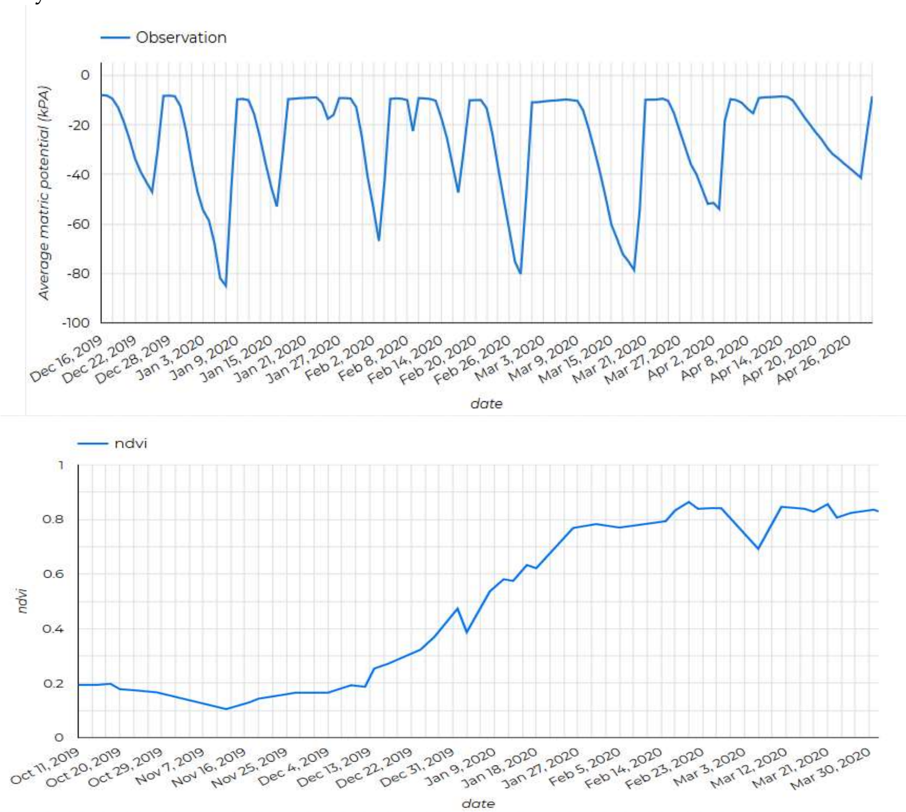

Figure 7. Soil matric potential (top) and the normalized difference vegetation index (NDVI) (bottom) monitored in one of the cotton farms over the crop season.

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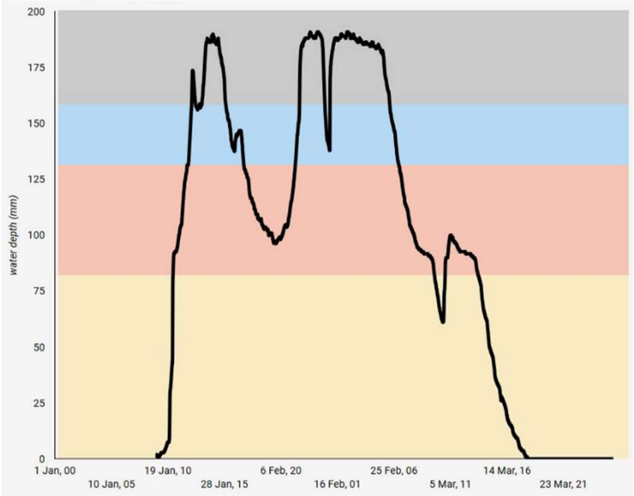

Figure 8 Daily water height monitored in a bay of a rice farm obtained from the multi-sensor capacitance probes.

3.1. Performance and Robustness of IRRISENS

As the IRRISENS platform is running on a commercial cloud, it is not relevant in this study to evaluate the overall performance of the platform since latency tests from GCS components would be related to the cloud infrastructure and not to the platform itself. The ASS (microservice) run within a configurable resources setup without elasticity but with maximum available resources configuration (cloud standard mechanism). In the following subsections, an empirical evaluation of the overall performance of the ASS is presented considering one that processes all data from the farm-focused specifically on the platform approach to deal with latency, robustness against failures, and data heterogeneity. The interaction between IRRISENS and irrigation control autowinches as an asynchronous and stateless service is also presented in following subsections.

3.1.1 Typical microservice in the cloud - resource allocation

All ASS instantiated in the IRRISENS platform has the same pre-configurable maximum resources in order to run. The most important resources are the maximum available memory and execution timeout, while the available CPU is controlled by the cloud. **Error! Reference source not found.** depicts a typical latency of an ASS microservice for a month. During this period, the ASS executed, and processed data collected from one farm every four hours. This ASS collected data from one of the farms, processed and cleaned data and composed a new crop model. Boxplots in Figure 9 indicate the daily processing time. It is clear to see that the latency fluctuates among days with significant variance. That was caused by the availability of resources in the cloud, particularly in the CPU at different times along the day. The evaluation of the latency of a heavy process performed by an ASS may be used to estimate the critical path regarding processing time of a complete flow as depicted in figures 5 and 6.

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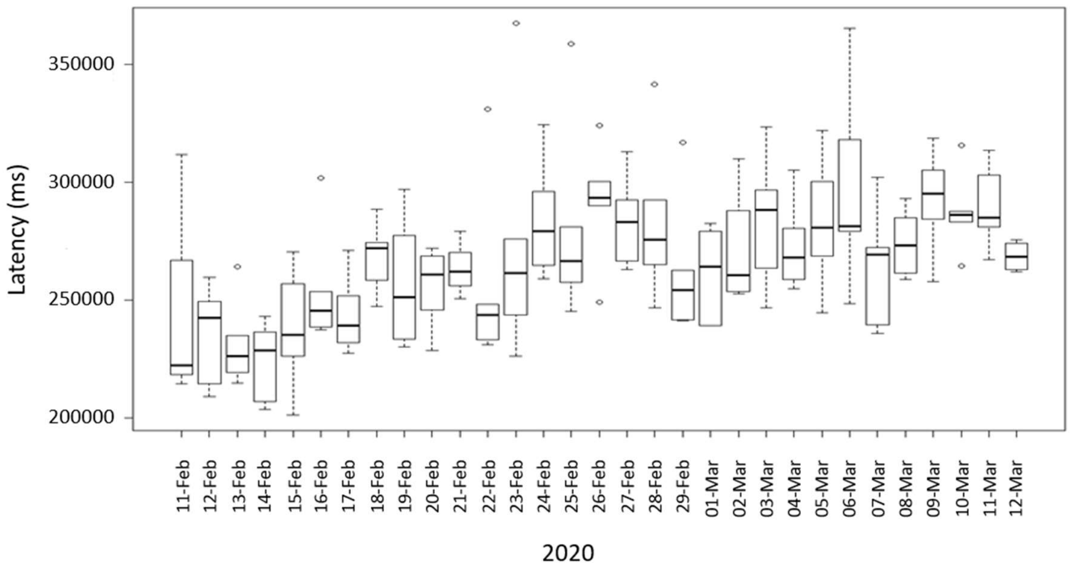

Figure 3 – Latency of an ASS for one month

The latency of the ASS depicted in **Error! Reference source not found.** when performing a heavy process was compared to the latency of an ASS performing a simpler task such as receiving data from the field, calculating the correct sensor values and storing data in the GCS cloud storage system (Figure 4). The latency in the ASS performing a simpler task fluctuated for a month between the 50s and 90s, while in the ASS performing a heavy process demanding more processing time the latency fluctuated between 200s and 330s.

3.1.2 Microservice robustness

There are several sources of failure in a daily monitoring activity of a commercial farm that can range from failures in the communication between the smart sensing device and the cloud, to malfunction of the equipment due to damage caused by adverse weather conditions or animals. In order to evaluate the performance of the microservices-based approach used in IRRISENS during potential failures, the "Crop parameter" ASS was designed to work following two different approaches: (i) as a monolithic service for all farms monitored and (ii) as one microservice for each farm. The ASS ran with the same resource configuration, so the performance would be affected as described in the previous section. Processes performed by the "Crop parameter" ASS were to collect and process all raw data from a farm, clean the new data, and update the dataset. All loggers sent the same kind of data and the similar number of parameters: in the cotton farms, each logger collected 39 sensor measurements per reading cycle while in the rice farms 37 measurements were collected per reading cycle.

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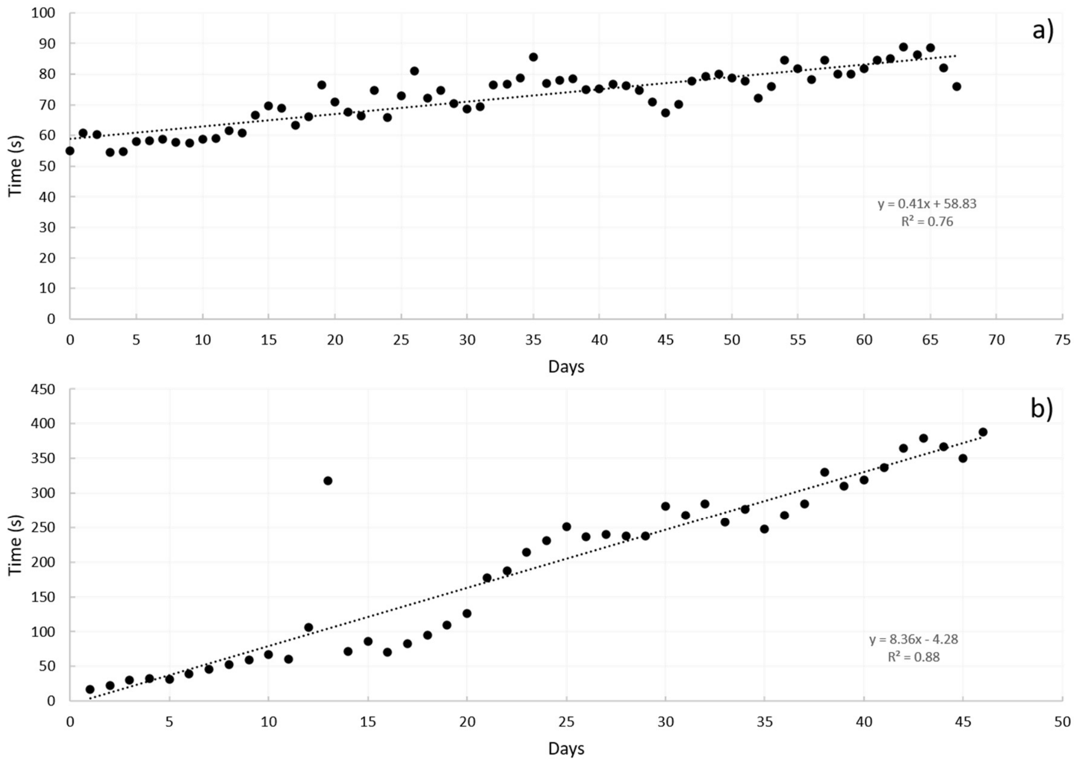

Figure 4. The latency of the ASS "Crop parameter" microservice in a rice farm when designed to perform individually for each farm (a) and as a monolithic service (b).

Daily linear increases in the number of points to be processed on each farm is expected due to the collect and process behaviours. Figure 4a depicts the processing time of the ASS “Crop parameter” microservice during the two last months of the growing season when designed to perform individually for each farm. Each point in the plot represents the processing time of the ASS microservice every 4 hours. Although there was a clear tendency towards a higher processing time as the season progressed, which was related to the availability of the resources in the cloud (lowest processing time occurred in most cases between 8 pm and 4 am), the increase in processing time was not significant. All the other microservices dedicated to monitoring a farm presented a similar behaviour and processing time as that illustrated in Figure 4 for the “Crop parameter” microservice (data not shown).

Error! Reference source not found.0b depicts the behaviour of a monolithic “Crop Parameter” microservice during the first eight weeks of the monitored season, i.e. one single service for all monitored crops. In the first 12 days, there were no failures in the field and most of the smart sensing devices collected data hourly. The processing time increased linearly up to day 16 when one of the loggers presented a failure and started to capture data more frequently. This failure was solved on day 25 causing the processing time to change substantially from around 70 s to 250 s. The immediate impact of this failure was that the monitoring time in all farms increased dramatically even with the problem that caused the failure was solved. The time needed to repair and solve issues depends on several factors such as distance to the farms (some monitored farms were more than 150km away from the maintenance team) and permission to access the area since treatments with agrochemicals may prevent access to farms at specific periods of the growing season. Although processing times oscillated during the season in both approaches tested (as individual microservices and as a monolithic service), in the monolithic approach, the processing time was drastically impacted by failures that occurred at any of the farms. The microservice-based approach followed in IRRISENS isolated failures that may occur in any individual farm, avoiding the performance of microservices

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in other farms to be affected. As an example, the last date of the monitoring period (end of the growing season), the processing time in the IRRISSENS microservice approach was around 75 s (Figure 4a), while in the monolithic approach the processing time at the end of the growing season based on the linear regression showed in **Error! Reference source not found.**0b was 1329 s.

3.1.3 Data Heterogeneity

In the context of the IRRISENS platform, data heterogeneity makes reference to two aspects: (i) the use of data collected from a same type of sensor to monitor different parameters according to the crop being monitored, and; (ii) the spatial and temporal resolution of data to be used to compose the IoT platform results.

The first situation is the case of the multi-sensor capacitance probe that in the cotton farms was used to measure volumetric soil water content while in the rice farms it was used to measure water height in the bays. The ASS "Crop parameter" microservice is setup during its instantiation when the type of crop is set up as a parameter. Figure 11 shows the raw data readings of a capacitance probe installed in rice (Figure 11a) and cotton (Figure 11b) farms for the same period of time (readings for 49 days) as well as the processed data used by the crop digital model. As the multi-sensor capacitance probe is not designed to compute water heigh, there were occasions in the rice farm when sensors readings were over 100%. As reported in [49], the microservice considers all sensors with readings higher than zero to calculate the water height. The model computation of those three signals generates the water height that it is part of the digital crop model (Figure 11a). In the cotton farm where the capacitance sensors were used for soil moisture monitoring, the raw data is first cleaned and then stored as parameters of the digital crop model. For the period shown in Figure 11b, there were no anomalies and therefore the cleaned data was the same as the raw data.

The transmitted data in both cases have the same format and reading limits, and the interpretation of these data may change according to the crop parameter passed into the ASS.

The spatial and temporal heterogeneity is handled by the digital crop model microservice which receives data from several sources, each one working at different time zones. In addition, the spatial resolution of the data is not the same given the nature of the service. Remote sensing data was obtained from satellite imagery. Images were available every 5 days from the Sentinel-2 satellite [52] in GMT time zone. Weather data was obtained in an hourly or daily basis while soil moisture readings were always obtained every hour. The microservice must interpolate and compose the remote-sensed data in order to be able to compose the digital crop model.

Table 1 shows the data obtained from the remote sensing Sentinel-2 platform and weather stations used to compose the digital crop model [46] [53]. To deal with spatial heterogeneity all data is GPS referenced to fit with the monitored crop area, and data is associated with the bay identification. The spatial and temporal resolution was harmonized taking into consideration the usage of the data. The remote sensing data were used to calculate parameters as Normalized Difference Vegetation Index (NDVI) and those data are interpolated to fulfil the missing days. The weather data are mainly used as parameters to calculate evapotranspiration (ETo). For that, the use of hourly data is relevant to calculate the estimated evapotranspiration and to feed it to the linear regression model used for forecasting, while the daily data is used as input in the same forecasting models to calculate the evapotranspiration one week ahead and support irrigation decisions.

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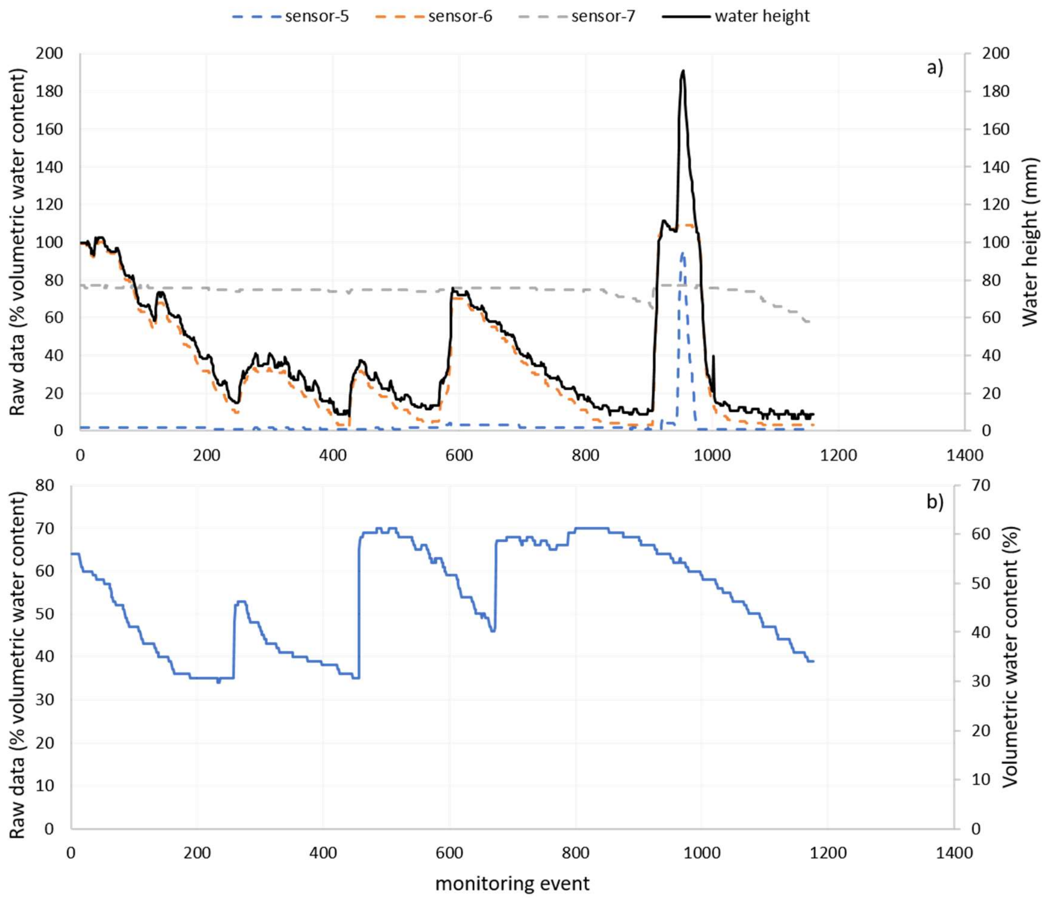

Figure 11. Raw data readings from the multi-sensor capacitance probes and processed data that is used in the digital crop model of a monitored rice (a) and cotton (b) farms during the same period.

Table 1 – spatial and temporal heterogeneity in remote sensing and weather forecast data

Crop Parameter	Temporal resolution	Spatial resolution	Parameter	Spatial resolution
NDVI	5 day	Bay area	Band 4	10m
			Band 8	20m
ETo	1 hour	Bay area	Temperature, humidity, wind speed	Farm area (local weather station)
ETo forecast	1 day	Bay area	Temperature, humidity, wind speed	City area

5.3 Irrigation control by IRRISENS

Automatic irrigation control in surface-irrigated crops remains a challenge because it is not possible to control all the irrigation parameters in a deterministic manner as done in traditional industrial control environments. Parameters important to irrigation planning such as precipitation can only be forecast and there is no guarantee that it may occur. Furthermore, the soil may be considered as a complex system [54] in which there are emergent behaviours that would be taken into consideration for effective irrigation control.

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The IRRISENS platform has a planning and irrigation control option that enables farmers/agronomists to monitor the soil moisture status or water heights at each bay as well as the status of the irrigation control autowinches, which means the percentage that equipment must open the door and start irrigation, as well as schedule an irrigation event. The platform has an ASS responsible to receive the irrigation planning information from the user and send it to the external cloud to do the effective control of the devices using a property technology. The ASS has an interface to a web service and a MQTT messages and sends a set of instructions to the devices in the field. Figure 12 illustrates the position of the irrigation control autowinches during an irrigation event and the evolution of the soil water tension measured at 0.20 m depth. The position 100% represents the gate at a fully opened state. The main channel gate must be fully opened during the whole irrigation event to enable water to access the different bays. Bay 1 is the first bay to receive water. When the gate between bays 1 and 2 opens, water in bay 1 flows to the next bay, which indicates the end of bay 1 irrigation. Evaluating the irrigation times for each bay it is possible to see that even after saturation was reached at 0.20 m depth as indicated by the sensors (soil moisture above -10kPa), the agronomist did not open the gate until seven hours later. The main gate remained open for 24 hours to irrigate the four bays.

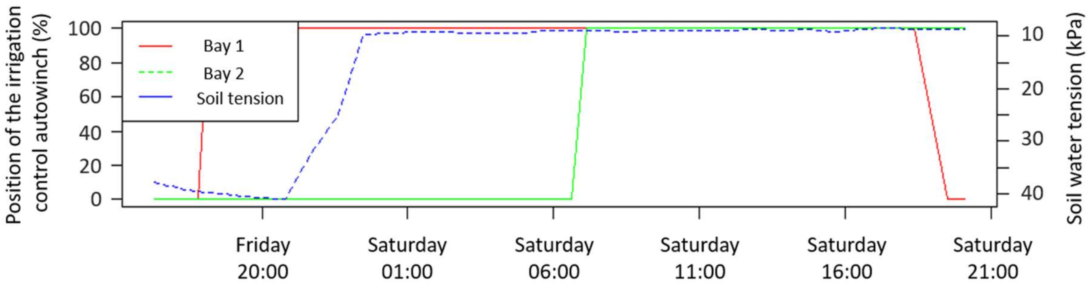

Figure 12. Position of the irrigation control autowinches (100% = fully open; 0% = closed) in bays 1 and 2

6. Discussion

This study proposed an evaluated an IoT platform based on fully replicable microservices used to sense and monitor soil, crop and weather data, forecast relevant parameters, interact with external (weather and remote-sensed data providers) and third-party cloud services for planning and scheduling irrigation at commercial scale. By implementing the IoT platform during the 2019/20 growing season at four farms growing two of the most important crops in the area, rice and cotton, this study identified five requirements that IoT platforms should meet when aiming to be used in agriculture at commercial scale:

1. Scalability
    - The platform should be able to sense, monitor, control and forecast data for multiple crops across multiple farms of varied size and nature.
    - Should be able to deal with different number of monitored farms or bays within farms across growing seasons.
    - Should be allowed to scale to changes in terms of the number of external services being consumed and the number of services being offered by the platform itself.
2. Flexibility
    - It must be flexible enough to collect at once varied data from each field with different monitoring requirements.

- Each crop may have a specific monitoring rate and sometimes some sensors need to collect more data at certain times so the IoT platform must be flexible to changes in monitoring rates.
- The platform should cater for different business requirements across commercial farms.

3. Heterogeneity
   - The IoT platform must be able to receive data from different sources and locations, each one with its own local time.
   - It must be able to deal with data heterogeneity when the same type of IoT sensor is used to provide different data depending on each farm needs (see section 3.1.3).
   - The platform should be able to integrate with heterogeneous communication technologies and protocols.
4. Robustness to Failure
   - The platform must be robust against communication failure that may happen due to extreme weather conditions or excessive distance between sensors and data receiving points. Intermittent communication failures may happen especially in farms located in remote areas.
   - The IoT platform must be also robust against unexpected failures of the IoT devices (malfunction, issues caused by animals, etc.) and must include specific procedures to monitor them.
   - Failures or changes in one farm should not compromise the applications of the platform to other farms.
5. Security
   - Data obtained from each farm should be isolated in storage and processing because of commercial privacy. Data transmission and storage should be secure from any vulnerabilities and cyber-attacks.
   - Each farmer/agronomist should be provided with a secure way to login into the platform and being able to share data when necessary with stakeholders, independent of their physical location or affiliation.
   - Farmers should be made aware of any data transparencies that might exist between the farm and the service providers.

The platform organized as microservices may prevent failures in one monitored area affect others, and it is an effective way to deal with heterogeneity. Using microservices associated with cloud services, such as messages and storage mechanisms create a dataflow where digital crop model is the digital representation of the physical environment under monitoring and control. Each independent dataflow receives data from the field and as crop parameter microservices has the mechanisms to prepare the data to digital crop model issues related to spatial and temporal heterogeneity and sensor readings can be solved in this element. Each monitored farm can deal with heterogeneity independently by selecting the proper microservice that represents the correct dataflow.

The IRRISENS architecture organization has the digital crop model and crop parameters as the critical elements, which is a remarkable difference compared to FIWARE based architecture as [11], [14] and [16] where the core element is the context broker and there are several structures that can store and handle data, each one based in its own data model. In [13] there are also several software units that store and manipulate data without a single unit as a digital crop model. Those IoT platforms do not necessarily have a dataflow structure for each monitored area. This distinction may be done in the case of FIWARE running one instance of the platform per monitored area.

As Agriculture 4.0 is related to the concepts of Industry 4.0. the IRRISENS architecture can be evaluated according to maturity level, since it presents computerization and connectivity as other IoT platforms, but contributes with visibility since the microservices and the resultant dataflow creates an independent digital crop model of each monitored area which could be considered the crop digital shadow. The IRRISENS platform also contributes to transparency because the digital crop model and the associated microservices produce knowledge about irrigation effects and dynamics since it is possible to evaluate the dynamics of the rice-growing and the ponded area using parameters such as evapotranspiration, NDVI and water heights, as well as soil moisture. The microservices may be organized. The use of weather forecasts and linear regression to evaluate crop parameters are still in an embryonic stage and cannot be considered as predictive capability and adaptability as presented in the Industry 4.0.

7. Conclusions

This work presented and evaluated the IRRISENS platform designed with a microservice-based architecture for monitoring, planning and scheduling irrigation at a commercial scale. Five main requirements for IoT platforms to be used in agriculture at commercial scale were identified from implementing the IoT platform in rice and cotton production: scalability, flexibility, heterogeneity, robustness to failure and security. The platform was able to address all these requirements.

The microservices that composes the data flow presented affordable scalability and adaptability to monitor four farms and two different crops, each one with its particularities. As ongoing work, the IRRISENS platform has several features to be designed to fit additional requirements, including a new set of ASS microservices to promote automatic control of irrigation gates based on crop parameters. To automatically control irrigation of broadacre crops at commercial scale, other parameters apart from those monitored in this study should be considered such as the farmer behavior and his/her objectives when triggering an irrigation event. This is because this decision is not always based only on the plant water needs and other aspects such as fertilizer application or availability of water should be captured as well.

The use of a standard ontology may be an important improvement to store data and correlate these with a common syntax that would be exchanged between platforms related to the same farm. However, an initial investigation indicates that the commercial platforms do not follow a common ontology, which highlights the importance to have microservices to act as the interface between the IRRISENS platform and external services. Future work for the improvement of the platform includes mapping farmer attitudes and using this knowledge in irrigation planning algorithms and also evaluating new approaches to identify the representative locations to install point source smart IoT devices in the field to represent whole irrigation bays parameters.

Author Contributions: Conceptualization, J.H. and R.F.M methodology, R.F.M and C.B.L. ; software, R.F.M and A.A.B.; data evaluation and validation, R.F.M, C.B.L and J.H.; writing—R.F.M, C.B.L.; writing—review and editing, R.F.M, C.B.L and J.H.; funding acquisition, JH. All authors have read and agreed to the published version of the manuscript

Funding: This project was supported by funding from the Australian Government Department of Agriculture, Water and the Environment as part of its Rural R&D for Profit program, AgriFutures Australia and the Cotton Research and Development Corporation.

Acknowledgments: Many thanks to Matthew Robert Champness for comments on the draft manuscript and suggested improvements which have improved the manuscript.

Conflicts of Interest: The authors declare no conflict of interest

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