Advancing IoT-Based Smart Irrigation

Rodrigo Togneri, Carlos Kamienski, Ramide Dantas, Ronaldo Prati, Attilio Toscano, Juha-Pekka Soininen, and Tullio Salmon Cinotti

Abstract

Integrated Internet of Things (IoT) platforms are needed for realizing IoT potential in commercial-scale applications. The main challenge is to provide solution flexibility to meet custom application needs. We developed an IoT-based platform for smart irrigation, with a flexible architecture to easily connect IoT and machine learning (ML) components to build application solutions. Our architecture enables multiple and customizable analytical approaches to precision irrigation, making room for the improvement of ML approaches. Impacts on different stakeholders can be anticipated, including IoT professionals, by facilitating system deployment, and farmers, by providing cost reduction and safer crop yields. Examples are given based on pilots in Europe and Brazil.

Introduction

Nowadays, the Internet of Things (IoT) has already left the state of an idea and has been applied in practical projects. The technical and application challenges are enormous since IoT platforms enable complex real-time control systems that combine the use of communication infrastructure, hardware, software, analytical techniques, and application knowledge combined into multiple layers. One of the key technical challenges is to realize the expected IoT impacts on systems, as IoT allows them to become service mashups, connecting things as services. Consequently, system development will become dynamic plug-and-play interoperable service composition, and system logic will become service orchestration. Overall, IoT allows solution flexibility to fulfill custom application needs.

In the context of agriculture, irrigation is a key task to guarantee adequate crop yield by avoiding under- and over-watering. Moreover, it is an important cost driver, as the energy to transport water and to operate irrigation equipment is costly — in some places, even the water itself is costly. Smart irrigation seeks to apply IoT and analytical methods to leverage precision irrigation, aiming optimal cost effectiveness to the farmer by flowing the water in the proper amount to places where and when it is needed.

In this article we introduce the concept of a flexible IoT-machine learning (ML) platform, wherein IoT and ML components are connected as services in an application context, allowing adaptable solutions to fulfill application needs. This approach benefits IoT professionals, as they can easily develop and deploy complex solutions involving devices, communication, data management, analytics, and application elements.

In particular, our work on this concept has resulted in a platform called SWAMP[1] that implements our flexible IoT-ML architecture toward the smart irrigation problem. This allows highly customizable soil water management solutions, involving flexible connectivity among data, physical models, and ML algorithms oriented to solve application key tasks, such as water need estimation and irrigation planning and operation. We call this concept flexible data-driven soil water management, which in practice allows suitable solutions to a great variety of soil, plant, and regional weather characteristics. This approach benefits the farmer, as a highly customizable smart irrigation solution may reduce water and energy usage and mitigate crop yield risks as it keeps soil water content at healthy levels for plants.

In the remainder of this article, we compare our approach to other practical IoT research projects, provide details on our flexible platform applied to precision irrigation, describe our flexible ML approach to address precision irrigation tasks, highlight the potential impacts of our approach to IoT professionals and farmers, and summarize our main contributions.

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Related Work

In recent years, different academic and commercial initiatives have emerged, aiming to incorporate IoT and ML into the agriculture. IoF2020 (www.iof2020.eu)[2] and Dragon (www.data-dragon.eu) are two projects funded by the European Union for developing IoT platforms for agrifood. IoF2020 is organized into five sectors that adopt different solutions: arable crops, dairy, vegetables, fruits, and meat. Arable crops use sensors to monitor production and intelligent analysis of images to assess crop development. GPS data from cattle neck collars or livestock movements monitor dairy chain, and ML is used for early lameness detection. IoT devices track the production chain of vegetables, fruits, and meat. Dragon aims to integrate IoT data with phenomics, genomics, and metagenomics data associated with ML methods to increase production.

Other recent academic studies include a platform for precision agriculture and experimentation in turmeric cultivation [1]. The platform provides a graphical interface for connecting sensors and actuators and uses analytical methods to analyze the delay of messages. Another study uses thermal images generated by drones and transmitted throughout a cloud-fog system to identify non-uniform irrigation zones [2].

Commercial companies are also putting some of these ideas into the market. Examples include Agrosmart (www.agrosmart.com.br) in Brazil, Agricolus (www.agricolus.com) in Italy, and Cropmetrics (www.cropmetrics.com) in the United States. Among other technologies, they use soil sensors, weather stations, and weather forecasts for irrigation advising. However, their underlying approaches for water need estimation and irrigation optimization and operation are not available.

Despite the richness of recent approaches adopting IoT in the agri-food chain, they do not yet fully explore: (a) the architectural aspects to hold flexible solutions involving IoT and ML components and (b) the potential of the collected data for a more accurate analysis of water needs. In this article, we advocate that data-intensive methods provided by ML algorithms, in combination with IoT technologies and weather-soil-atmosphere simulations, can provide a considerable impact in precision irrigation and its solution deployment.

A Flexible IoT-ML Platform for Smart Irrigation

The success of next generation systems for precision irrigation based on IoT technologies coupled with intelligent ML data processing techniques depends on the ability of the solution to adapt to different contexts found in farms. A flexible IoT-ML platform must allow different deployment configurations of hardware, software, and communication technologies, customized to deal with the requirements and constraints of different settings, countries, climate, soils, and crops. Here we advocate that an IoT-ML infrastructure for providing smart irrigation services be defined by two complementary dimensions,

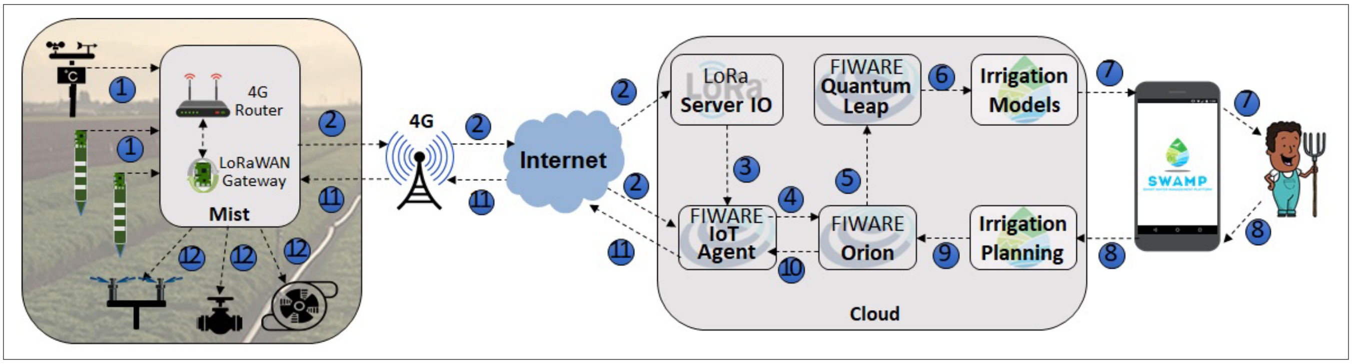


FIGURE 1. IoT-ML platform overview and end-to-end data path for a smart irrigation scenario.

namely core components and deployment locations. Core components are a set of software, hardware, and communication technologies, such as soil moisture sensor probes, long-range WAN (LoRaWAN) [3], Message Queuing Telemetry Transport (MQTT) [4], LoRa Server (www.loraserver.io), FIWARE [5], and SEPA [6], as well as specific services for water need estimation and irrigation planning and operation.

On the other hand, deployment locations define where core components can be placed, and how they communicate with each other. This generates distinctive configuration scenarios for different deployments. Locations follow an IoT computing continuum, composed of things (sensors and actuators), mist (field nodes such as radio gateways), fog (farm on-premise computing infrastructure), cloud (data storage and processing), and terminal (a smartphone, tablet, or laptop where the end user interacts with the application). The five instances of this continuum define the end-to-end information path starting with data collected by sensors up to commands executed by actuators. The five instances might not necessarily be present in all scenarios. Rather, depending on farm characteristics, requirements, and constraints, fog or cloud may not be present. This feature provides additional flexibility to the IoT-ML platform, as the differences are understood, and the platform adapts to the farm and not the opposite.

Figure 1 depicts the IoT infrastructure for providing smart irrigation services, composed of core components and deployment locations. In smart agriculture, each farm has particular objectives and characteristics, so different deployment configurations may be used, representing instances of the same platform. Figure 1 presents a simpler version of the deployment of the IoT-ML platform where locations are thing, mist, cloud, and terminal (i.e., no fog is used). This configuration was chosen for simplicity and a farmer's choice of not hosting any on-premises infrastructure.

In Fig. 1, the numbers in blue circles represent a simplified sequence of the end-to-end data flow through this deployment of the IoT-ML platform. Soil moisture sensors send data via LoRaWAN to the gateway installed in the mist node. Particularly for the SWAMP Project, we have built a custom-made three-depth soil moisture sensor, but also use commercial sensors from Libelium (www.libelium.com) and Meter (www.metergroup.com). A weather station also sends data to the mist node via a serial wired interface (1). From there, the mist node forwards data via 4G through the Internet directly to the cloud (2).

Within the cloud, sensor data are treated by the LoRaWAN server and sent to the IoT protocol translator (3), such as a FIWARE IoT Agent. Weather data goes directly to the IoT protocol translator using the Ultralight 2.0 protocol, as well as weather forecasts obtained from an external service. The Translator converts the three different types of input data — soil, weather conditions, and weather forecast — into the format of the particular IoT underlying platform transmitting them to the context broker (4) (e.g., NGSI JSON format for FIWARE Orion). Once data arrives at the context broker, it is forwarded to time series storage (5) that makes it available for further processing (e.g., FIWARE QuantumLeap using CrateDB), where the first part of the end-to-end data flow ends. Here, depending on the volume and velocity of data, the time series storage may be replaced by a distributed data pipeline (e.g., Apache Kafka) connected to a big data processing system (e.g., Apache Spark). However, for most smart agriculture scenarios dealing with individual farms with hundreds of sensors, time series storage is a lightweight solution that provides adequate performance.

The water need estimation component obtains soil moisture, weather conditions, and weather forecast data from the time series storage (6) to generate ideal crop water need estimates. Water need estimation is further divided into physical and ML models, further explained in the next section. The estimates are in turn used by irrigation planning to generate an optimized and real plan that is aware of different physical and financial constraints (7). Farmers are shown the irrigation plan via the Farmer App (8) and approve or change the irrigation plan that is sent back to irrigation operation (9), which controls the irrigation system. From there, irrigation commands follow the way back to the mist going through the context broker (10), IoT protocol translator (11), and Internet/4G (12). Finally, irrigation commands reach sprinklers, pumps, and valves (13).

Should the fog be present in a different scenario, the end-to-end communication would be preserved with small changes, as some components would be deployed on-premises in the farm office where the fog node is located, such as the LoRaWAN server. This scenario includes the direct operation of the irrigation system. In alternative scenarios, the irrigation plan either interacts with existing third-party irrigation systems (e.g., Netafim — www.netafim.com — or Focking — www.fockink.ind.br) already installed on the farm or even used by farmers to operate the irrigation systems manually. These options for interacting with an irrigation system are common, and we assume they are generic enough to represent an IoT ecosystem for smart irrigation.

Flexible Data-Driven Soil Water Management

Over the last decades, data-driven soil water management has been accomplished using physical models[3] or triggering soil moisture sensors data[4] [7]. However, as IoT enables more abundant data, with major spatial and temporal granularity and low latency, it increasingly allows the rise of data-driven approaches. Here, a key challenge is how to make all analytical techniques (e.g., physical models and ML) available to work together in a flexible IoT platform, considering that each crop, type of soil, and region may demand a different solution. In this sense, our work aims to show the roles that these analytical techniques can play in soil water management, and how they can be flexibly assembled together. Our approach is based on two main characteristics:

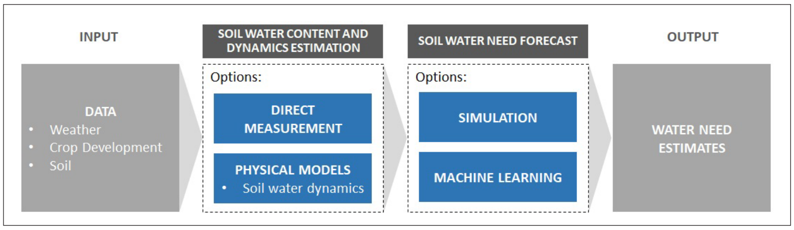


FIGURE 2. Water need estimation process.

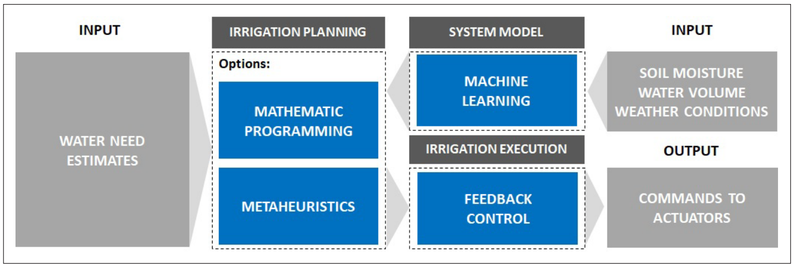


FIGURE 3. General data flow between irrigation services.

- Solution flexibility: Modularized components are integrated as services in the IoT platform, allowing solution flexibility.
- Increased ML relevance: Analytical solutions can be assembled from traditional physical approaches, and modern ML and simulation ones, and even by combining them. Benefits of this approach are not only improved irrigation plans, but also self-improved platforms that learn from experience.

Soil water management is performed in two phases, namely water need estimation and irrigation planning.

Water Need Estimation

The precision irrigation problem can be modeled as the soil water balance system at the root zone, where the soil water content is the result of the balance between water content level and a series of mechanisms that make this level increase or decrease (soil water dynamics) [8]. IoT provides the ability to monitor water content levels and dynamics, while soil water management systems seek to maintain water content in an optimal range [7].

Figure 2 depicts the water need estimation process, divided into two key activities:

- Soil water content and dynamics estimation: This consists of estimating soil water content and dynamics through:
  - Direct measurement of soil water content, rainfall, irrigation, and so on
  - Physical models of soil water dynamics applied over the collected data (weather data mainly) and soil and crop characteristics
- Soil water need forecast: This consists of calculating soil water content forecasts and water need forecasts for each moment of a planning horizon, using techniques such as simulation and ML algorithms:
  - Simulation is appropriated when working with physical models, iteratively applied to simulate future data points [9].
  - ML takes advantage of data from multiple time series (soil moisture, soil water balance, soil characteristics, and weather data) of direct sensor readings or from variables derived out of physical models. Weather forecast data, provided by external services, can also be used. Different multivariate forecasting methods can be used to handle these multiple time series [10, 11].

The process depicted in Fig. 2 allows flexibility once it allows different components combinations, as they are implemented as services in the platform. It is also possible to customize each combination, as they have numerous options inside them (i.e., different physical models and ML techniques).

As an example, the SWAMP project provides two customized analytical solutions among all combination possibilities to fit the characteristics and needs of different pilots. One of them, called CRITERIA-1D [9], uses physical models and simulation, wherein soil water dynamics models (physical models) are the input to soil simulation that generates soil water content and water need forecasts. Another solution uses direct measurements, physical models, ML, and simulation, wherein the main input is direct measurement of soil moisture enriched by an evapotranspiration[5] model (physical model) [7] as the main soil water balance contributor. ML techniques[6], such as Panel VAR [10] and RNN-LSTM [11], are used for the processing of soil water content and water need forecasts, and simulation to test alternative irrigation scenarios. Note that the latter uses Panel VAR and RNN-LSTM, respectively, a traditional and a cutting-edge technique for time series, thus highlighting the solution flexibility in exploring different ML techniques as they gain relevance.

Irrigation Planning and Operation

The water need estimation models provide what can be called the ideal irrigation. There are, however, other aspects that need to be considered when conceiving an actual irrigation plan, that is, a plan that can be put in place in the farm, which include:

- Water availability: Water scarcity is a problem in various parts of the planet. Water quotas or supply schedules might not allow the ideal amount of water to be irrigated in time. If the needed amount of water is not available, the irrigation plan should allocate the existing water so that the best economic return to the farmer is achieved.
- Costs of irrigation: Even if the water comes from private reservoirs, irrigation is not free. Pumping the water to the fields consumes energy, and its cost has an impact on the farmer's bottom line. For example, in certain regions of Brazil, the energy bill can account for up to 30 percent of the production cost. A cost-aware plan should avoid irrigation when tariffs are higher.
- Limitation of the irrigation systems: Irrigation methods differ in how much of the irrigated water actually reaches the plants: furrow irrigation has 60 percent efficiency, while sprinkler irrigation reaches 75 percent [12]. Other aspects of the irrigation infrastructure need to be considered when planning: maximum pumping capacity of the farm, uniformity of irrigation, and soil variability, among others.

Figure 3 presents a modular approach that separates irrigation planning from operation, completing the data flow shown in Fig. 2. There are three main modules:

- Irrigation planning: Computes the timing and water volume of irrigation events that best address the crop needs, while being aware of operational constraints and economic interests. Linear and nonlinear programming techniques can be used, as well as approximate solutions such as those provided by metaheuristics [13].
- Irrigation operation: Communicates with the sensors and actuators installed in the farms, sending commands and monitoring the operation to ensure adherence to the plan. It controls the opening and closing of valves, the pressure at pumps, and so on, using the underlying IoT communication infrastructure to send commands. The use of standard IoT interfaces and protocols enables on-demand addition of sensors and actuators, smoothing the transition toward fully automated irrigation.

- System Model: Computes an updated model of the system behavior as far as irrigation is concerned. IoT devices (e.g., soil sensors, water meters) in combination with data-driven techniques enable estimating the actual irrigation efficiency, and planning accordingly.

Discussion and Lessons Learned

Physical Models vs. Machine Learning

The increasing use of IoT in precision irrigation brings spatial and temporal accuracy gain, as sensors can potentially be placed in all manageable locations on a farm. Thus, site-specific particularities can easily be considered, leveraging the exploration of data-driven approaches. In this context, the question of what would be the right combination of techniques to deliver adequate soil water management emerges. Do traditional approaches, such as using physical models or triggering soil moisture sensors data [7], still take place? Or is this the time to avoid physical models and use cutting-edge ML algorithms acting directly to data?

Our vision is that there is no unique ideal analytical approach for all cases, as crops differ significantly in irrigation methods and in crop, soil, and regional weather characteristics. More than that, depending on crop culture or region, not all data features might be available or cost-effective. However, a discussion of the roles traditional and ML approaches can play in effective solutions can provide guidelines to discern the most appropriate alternatives to each application case.

Physical models have been extensively used in irrigation, bringing implicit agronomic knowledge, as they connect raw data features to specific and relevant features. Nevertheless, there are important limitations, as general models involve simplifications that often ignore local particularities, while site-specific models work well only regionally, and few models have adequate performance levels for different regions. Finally, the few models of general application that are flexible enough to address different conditions [7] are often complex and require many data features that are difficult to obtain.

On the other hand, pure ML approaches applied directly to IoT data seem promising, as cutting-edge deep learning is capable of capturing implicit knowledge from raw data in many application areas, as well as delivering highly customizable results [14]. For this reason, we believe that ML approaches will be extensively explored in scientific research in the coming years, allowing the emergence of truly cognitive smart irrigation systems. As such, our architecture approach, based on core components and deployment locations, gives the necessary flexibility not only to build customizable IoT-ML solutions, but also to assemble customizable data-driven solutions. For smart irrigation, we have shown that it is possible to use various combinations of analytical tools, including mixes of physical models, simulation (traditional approaches), and ML techniques.

As ML gains momentum, existing physical models may lose room because ML could implicitly capture from raw data the same information physical models provide. Instead, IoT's continuous growth might enhance the utilization of physical models, as they can calculate their outputs with better spatial and temporal granularity. Also, IoT tends to promote not only physical models but also ML. In summary, a futuristic vision may be that ML is well positioned for IoT-based applications. However, although ML seems to have a promising future for smart irrigation, we are still at the beginning of its exploration, and we need reliable data that now is still generated by physical models or a combination of data and ML techniques.

All in all, considering the advantages and disadvantages of each side, we advocate that current solutions consider using both physical models and ML algorithms — physical models serving as feature engineering for ML approaches. We believe that physical models can aggregate agronomic knowledge that ML algorithms eventually cannot capture yet directly from raw data. Finally, as different physical models can potentially capture different aspects of reality, we recommend using multiple physical models, even for similar tasks. Then ML will hold the task of capturing valuable information from the features provided by the physical models to deliver more precise water need estimation.

Integrating Different Stakeholders

The approach taken is the result of a joint and largely interdisciplinary effort, and the authors' ambition is to generate an impact on a wide community of stakeholders with the envisioned innovation. On one hand, the interoperability at the communication level provided by IoT is a key factor to promote a platform culture among not-computer-scientists, as it brings easy node deployment, data collection, and inter-researcher interaction. On the other hand, only with our flexible architecture approach due to the heterogeneities embedded in the agricultural scenario — heterogeneity of devices and simulation tools, but also farms and the stakeholders themselves — can the barriers be properly handled. Different stakeholders speak their own languages: for example, soil-moisture sensor data are numbers for computer scientists, bits for telecommunication professionals, voltage signals for electronic engineers, while the end users expect volumetric soil moisture values. As the calibration of these sensors is soil-type-dependent, geologists, agronomists, and other researchers must take part in the game of this context-dependent calibration process.

Altogether, the smooth interplay between actors with different skills and habits is a key success factor. Each stakeholder needs specific and mostly mobile services, with the appropriate human-machine interface, if we want to deploy the appropriate level of automation with the man in the loop, as required in today's agriculture. Services need to be organized like a chain of tools that mutually exchange information and understand each other thanks to a shared information model based on emerging ontologies. This shared data model fosters smooth and sustainable innovation because the tool chain may easily be extended to provide new capabilities and value propositions, and attract new stakeholders.

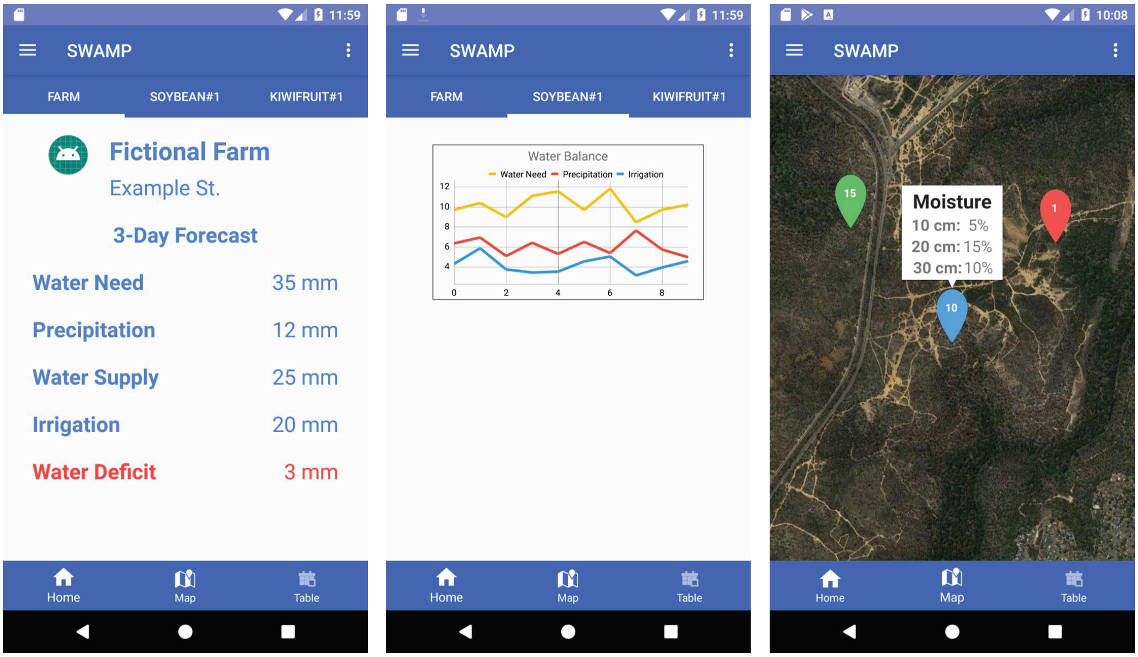
Impacts

For IoT Professionals

Our approach incorporates the ML pipeline into the IoT continuum by using a structure of services deployed as containers that exchange messages through the FIWARE NGSI unified data model. This scheme impacts IoT platform development and deployment in many aspects:

- Automation: The platform provides a subscribe/notify mechanism for building automated data pipelines.
- Traceability: The storing of meta-data information about the model specifications and context of data used in the estimation allows keeping track of model forecasts, as well as quality indicators.
- Pluggability: The integration of new or updated models is facilitated by the unified data model, consuming data and producing water need estimates in a standard way.
- Flexibility: The pluggability allows IoT professionals to compose different data workflows flexibly by using various components.
- Hybrid environments: The architecture allows the use of different ML frameworks to train models, as well as hardcoded physical models.

All these aspects have been allowing a relatively simple deployment of our platform in all SWAMP pilots, each one with its characteristics and different specific goals. In Italy, the goal is to use farm data for water management and distribution (i.e., to share data outside the farm to create an even bigger system-of-systems). In Spain, the goal is to explore the limits of flexibility and precision in irrigation by going into a very fine-



a) Summarized overview b) Water balance chart c) 3-depth soil moisture sensor

FIGURE 4. Farmer application screenshots.

grained irrigation system where each sprinkler is an IoT node. In Bahia, Brazil, there is a large-scale use case with huge center-pivot irrigation systems, where the goal is to decrease operational costs through improved situational awareness. Near São Paulo, Brazil, the goal is to improve the quality of grapes and wine.

For Farmers

Currently, in modern farms that rely on physical water need estimation models and respect soil variability, farmers are provided with irrigation plans for long periods, such as weeks, months, or even the entire season. Based on their accumulated experience and daily work in the field, they continuously adapt the irrigation plan to avoid crops suffering from water stress. In this scenario, the irrigation plan plays the role of an offline longer-term forecast that needs to be fitted into the reality of the farm. In a fully automated future agriculture scenario, the IoT-based smart irrigation system will precisely control every aspect of the use of water, adapting it to shorter-term periods according to instantaneous information coming from the field, which can be daily or even based on intra-day micro adjustments in the irrigation plan.

Between these two scenarios — current and future — lies a new IoT-enabled reality that will change the way farmers face irrigation. In any case, a requirement is that farmers always control the irrigation and are provided a wealth of real-time information to be able to make better decisions. To this end, we developed a smartphone app (Fig. 4) where farmers are informed of immediate water needs (Fig. 4a), measured and forecast water balance time series (Figure 4b), and the current soil moisture information for a 3-depth sensor probe (Fig. 4c). With this real-time status of the farm at hand, and equipped with the optimized irrigation plans computed by the system, the farmer can achieve better use of the water resources without harming productivity.

As the system reliability and precision increase and earn the trust of farmers, they can slowly give more power to the system to make automated decisions. In other words, the application will allow farmers to express policies on how to behave whenever a new irrigation plan is generated.

Conclusion

In this article, we present our flexible IoT-ML platform and highlight its scientific contribution over related work. The platform allows easy solution deployment involving IoT and ML components working in an application. Our real case is a smart irrigation application, where we exemplify how a solution can be built and customized depending on site-specific needs. Special attention was given to how the platform enables more exploration of ML-based solutions and on how it can positively impact IoT professionals' and farmers' needs. SWAMP project pilots have just been deployed; they are operating properly, and data is being collected. The next step, expected by the end of 2020, is to analyze the data and disseminate quantitative impact results.

Acknowledgments

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Biographies

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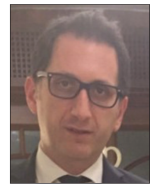

Attilio Toscano (attilio.toscano@unibo.it) is a hydraulic engineer with a Ph.D. in environmental engineering, and an associate professor of agricultural hydraulics and watershed protection at the University of Bologna. His research activity is mainly focused on sustainable agricultural water management, precision irrigation, and NBSs (constructed wetlands) for wastewater treatment and wastewater reuse in agriculture. He was/is involved in national and European projects as WP leader or coordinator (SWAMP, MEDIWAT, CHEM-FREE, WATER4CROPS, FIT4REUSE, GREEN4WATER).

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Footnotes

[1] SWAMP (www.swamp-project.org) is a European Union and Brazil research partnership that holds a pilot project to explore alternatives for implementing IoT into different types of environments and irrigation systems [15].
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[4] Soil moisture sensors are monitored. When the water content approaches a critical level, an automated trigger starts the irrigation process.
[5] Evapotranspiration is the main water consumption physical process, combining evaporation from soil and plant transpiration [7].
[6] Panel VAR (Vector Autorregressive) and RNN-LSTM (Recurrent Neural Network, using Long Short-Term Memory architecture) are time series machine learning techniques.