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RESEARCH ARTICLE

COSMIC-SWAMP: IoT Processing of Cosmic-Ray Soil Moisture Sensors

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ABSTRACT Cosmic-ray neutron sensing (CRNS) has emerged as a promising technique for non-invasive, field-scale soil moisture monitoring, offering advantages over conventional point-based sensors. However, the practical use of CRNS data in operational smart irrigation systems remains challenging, particularly due to the lack of IoT platforms and frameworks capable of automatically ingesting, calibrating, fusing, and analyzing CRNS measurements in real deployment settings. This paper addresses this gap by presenting COSMIC-SWAMP, an IoT platform and analytics framework designed to operationalize CRNS-based soil moisture data within smart irrigation environments. The proposed framework integrates heterogeneous sensing technologies and communication infrastructures, enabling automated data ingestion, environmental correction, calibration, spatial and temporal data fusion, and forecasting-based analytics at the level of irrigation management zones. A real-world deployment combining LoRaWAN-connected prototype CRNS sensors and a co-located commercial reference system is used as a proof of concept to validate the framework's feasibility and flexibility under operational conditions. The evaluation demonstrates that COSMIC-SWAMP can harmonize heterogeneous soil moisture data streams, generate consistent volumetric water content estimates, and support automated analytics workflows for irrigation decision support. While this study focuses on system and framework-level validation rather than exhaustive metrological assessment of sensing technologies, the results highlight the potential of COSMIC-SWAMP to enable scalable and sustainable integration of CRNS data into IoT-based smart irrigation systems. Limitations and directions for future measurement campaigns and extended validation are discussed.

INDEX TERMS Smart irrigation, Internet of Things, cosmic ray neutron sensors, soil moisture sensors, LoRaWAN.

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I. INTRODUCTION

Continuous soil moisture monitoring in arid and tropical regions is a major challenge. Effective irrigation decision-making, based on data-driven modeling, relies on representative soil moisture measurements over large sites [1], [2], [3]. Historically, soil moisture has been measured in situ using invasive multi-depth sensor probes installed directly into the soil. Reliance on in-ground sensors (e.g., time-domain reflectometer probes or capacitive sensors) within the field presents different challenges to collecting reliable data [4].

Individual sensors typically provide point measurements that do not accurately capture the changing soil dynamics typical across field scales [5]. Although satellite products have been offered as a solution to this problem, freely available products often have temporal resolutions too low for precision irrigation management [6]. While upscaled, higher-resolution data products can be purchased, they can have much higher per-hectare costs than in-situ sensing arrays. Furthermore, sub-kilometer products that are available typically still require networks of ground sensors or extensive ground calibration campaigns to build empirical models of soil moisture [7]. These empirical models require a high level of a priori knowledge for a given site to avoid high daily soil moisture uncertainty. Several smart farm deployments have considered using Internet of Things (IoT)-enabled devices to transmit data wirelessly, thereby easing the deployment and in situ data collection. The lack of reliable soil moisture time-series data from small point-probe arrays is expected to compromise the accuracy of data-driven water-need estimation models for modern deep learning architectures. Cosmic rays offer a unique solution for measuring soil moisture at the field scale, which could support effective irrigation management in the future. The Cosmic Ray Neutron Sensing (CRNS) [8] method uses neutrons coming from the soil to non-invasively estimate soil Volumetric Water Content (VWC), the ratio of the volume of water to the volume of soil, which is a common measure of soil moisture [9]. When high-energy cosmic ray neutrons come from the upper atmosphere [10], their subsequent products [11] are either reflected from the ground or go on to produce secondary neutrons. Since hydrogen acts as a strong neutron moderator, neutrons generated in the atmosphere or soil are slowed and absorbed when they encounter water. As a result, the total neutron rate observed by neutron sensors placed above the ground is inversely correlated with soil moisture in the local vicinity of a sensor [12]. Due to the long path length of neutrons in air, the effective footprint of such a sensor can range from 120 to 275 m in radial distance, depending on local conditions [13]. The sensing depth of the technique in soil has been found to range from 15 to 75,cm from the surface [14]. Several cosmic ray soil moisture monitoring networks are currently operating globally, such as COSMOS [15], CosmOz Australia [16] and COSMOS-UK [17], which primarily use Helium-3/BF_3-based detector systems. To date, CRNS networks have been primarily used for hydrological monitoring research. However, recent initiatives have looked at the use of CRNS for monitoring and optimizing agricultural water use [18], [19], [20], [21]. Beyond understanding the fundamental limitations of the technique, another challenge in achieving this goal is integrating cosmic ray sensor data directly with irrigation systems. Deployments in farming contexts typically require farmers to either manually retrieve raw data from field sensors and process it offline or download it from FTP servers. This necessitates additional processing steps to correct for local conditions and average data over a daily period before it can be used to assess field moisture levels. Whilst some CRNS providers support data acquisition via dedicated servers, the processing steps in these solutions are typically closed-source. Currently, there is no open-source solution for research on data-driven irrigation that can automatically calibrate and correct cosmic-ray sensor data and integrate it into large-area agri-sensor networks in a plug-and-play fashion. Similar to the capacitive sensing case, it is expected that manual calibration measurements post-deployment are necessary for the reliability of cosmic ray neutron sensors to reach the level of precision needed for accurate crop modeling inputs, and therefore, further development of community tools to support automated calibration by novice users is needed for these to be seriously adopted in these fields.

This paper describes the development of a prototype Internet of Things platform, COSMIC-SWAMP, which addresses this problem by building on previous efforts to develop a module smart water management platform (SWAMP) [22] using traditional in-ground capacitive sensing probes. By enabling the seamless deployment of cosmic-ray neutron probes in agricultural environments and automating calibration and water-content extraction, COSMIC-SWAMP provides a plug-and-play solution for monitoring irrigation systems. Measurement and simulation results show the effectiveness of the COSMIC-SWAMP approach for CRNS-based smart irrigation. The focus of this research is on the architecture of such a system and the components required to integrate cosmic-ray sensor systems into large-area monitoring networks reliably.

Despite the increasing interest in cosmic-ray neutron sensing (CRNS) for field-scale soil moisture monitoring, the practical integration of CRNS data into operational IoT-based smart irrigation systems remains an open challenge. Existing studies predominantly focus on sensing principles, calibration, or offline data analysis, while IoT platforms for smart irrigation typically rely on conventional point-based sensors or remote sensing products and do not natively support CRNS data streams. This gap hinders the scalable, automated, and long-term use of CRNS measurements in real agricultural deployments.

The problem addressed in this work is how to operationalize CRNS-based soil moisture measurements within an IoT platform that supports automated data ingestion, calibration, fusion, and analytics, enabling their use in irrigation decision support systems under real deployment conditions.

The main contributions of this paper are as follows:

- The design and implementation of COSMIC-SWAMP, an open and extensible IoT platform that enables the operational integration of cosmic-ray neutron sensing (CRNS) data into smart irrigation systems.
- A modular IoT analytics pipeline supporting automated data ingestion, environmental correction, calibration, spatial fusion, and forecasting of soil moisture at the level of irrigation management zones.
- A system-level validation through a real-world deployment combining heterogeneous CRNS devices and communication infrastructures, demonstrating feasibility, interoperability, and automated operation under practical conditions.
- A qualitative and quantitative evaluation framework that highlights the strengths, limitations, and challenges of using CRNS data within IoT-based irrigation decision support.

Farmers and end-users can benefit from research on CRNS for soil moisture measurements and from the COSMIC-SWAMP platform, as both have the potential to improve smart irrigation substantially in the future. As a field-scale non-invasive technology, CRNS could replace both point-based measurements. Point-scale in-situ sensors must be installed in complex networks to provide representative soil moisture values that capture the spatial soil variability of different management zones within a parcel. Sensors must be installed and removed periodically, depending on the crop. On the other hand, large-scale remote sensing from satellite or uncrewed aerial vehicles lacks the temporal and spatial resolution for the relevant size of agricultural management zones, and it is constrained to measure only the very topsoil. While the CRNS technology overcomes these limitations, contributions to advance technology transfer in this area, such as COSMIC-SWAMP, are required to make it reliable and affordable.

The remainder of the paper is organized as follows. Section II reviews related work. Section III describes the original SWAMP platform upon which the COSMIC-SWAMP platform is built. Section IV describes the cosmic ray sensing technique and volumetric water content extraction procedures in more detail. Section V describes the overall structure of the COSMIC-SWAMP platform. Section VII shows the results from the first COSMIC-SWAMP pilot study, as well as simulation results. Finally, Section VII reviews the potential impacts of COSMIC-SWAMP and areas for further research.

II. RELATED WORK

In recent years, there has been an increasing interest in developing IoT Platforms for various applications, including agriculture, which do not involve the use of CRNS. These platforms present varying interoperability and performance features [23]. They are required due to the inherently distributed nature of IoT-based smart agriculture, which must deal with a geographical and computing continuum spanning from sensors to the cloud, passing through multiple stages of fog and edge computing nodes [24], [25].

Benyezza et al. [26] developed a generic IoT platform for environmental and agricultural applications that handles typical data, such as air temperature, humidity, and soil moisture. The authors customized their platform for data fusion using fuzzy logic, tested it in a laboratory testbed rather than in an actual agricultural field. Comegna et al. [27] presented an IoT system for soil moisture, focusing on the multi-parameter sensor itself and on relationships among soil moisture, soil water content, matric potential, and hydraulic conductivity. Salam [28] presented several features of an IoT Platform for soil moisture measurements and radio communication evaluations, focusing on a wireless underground sensor network, and acknowledged that CRNS could provide complementary soil moisture measurements. Qian et al. [29] surveyed IoT-based smart irrigation systems covering various platforms and soil moisture measurement systems. Morchid et al. [30] presented a smart irrigation application based on the ThingsBoard IoT Platform, focusing on user-related features such as visualization and notification. Srinivasu et al. [31] investigated the use of explainable artificial intelligence (XAI) in smart agriculture and compared techniques to recommend suitable crops to specific farms. However, they neither focused on irrigation nor built an IoT Platform, instead using existing datasets.

Recent studies have also explored the integration and complementarity of emerging soil moisture sensing technologies in agricultural contexts. Gaspar et al. [32] investigated the combined use of proximal gamma-ray sensors and cosmic-ray neutron sensors to characterize soil moisture dynamics in an agricultural field in Spain, demonstrating the benefits of multi-sensor approaches for improving spatial and temporal soil moisture characterization.

In parallel, alternative approaches based on remote and proximal sensing have been explored to improve soil moisture mapping at field scale. Díaz-Delgado et al. [33] analyzed the use of uncrewed aerial vehicles (UAVs) for soil moisture mapping, highlighting both the opportunities and the challenges related to spatial resolution, calibration, and data integration when compared to in-situ sensing techniques.

More broadly, recent surveys have emphasized the increasing diversity of soil moisture monitoring approaches, spanning in-ground sensors, proximal and remote sensing technologies, and artificial intelligence-based data processing. Gautam et al. [34] reviewed advancements in soil moisture evaluation methods, stressing that effective agricultural decision support increasingly depends on the integration of heterogeneous sensing data and analytics frameworks rather than on individual sensing technologies alone.

Because the CRNS technique is relatively new, none of these studies has had a major focus on integrating neutron sensing of soil moisture into their networks, and no open source solution is currently available for such a direct integration. The majority of agriculture-based studies to date have focused on the feasibility of CRNS for irrigation scheduling, showing strong potential, but not necessarily on the integration challenges needed for sustainable, long-term adoption of the technique within the agriculture sector. Heistermann et al. [35] presented a dataset of a dense CRNS network spanning three years of measurements in northern Germany (from 2019 to 2022), collected from various CRNS sensors from different vendors. As the authors emphasize, they expect this dataset to be helpful to the scientific community in further research efforts. Zhang et al. [36] reported an experiment conducted to assess the applicability of CNRS for soil moisture measurement in a mountain area in northern China, concluding that CNRS can be used to measure soil moisture accurately in rocky areas, particularly in dry environments with low biomass. For extreme conditions and organic soils, there might be open questions, though Wang et al. [37] identified deviations during the frost period.

Emamalizadeh et al. [38] compared remote sensing and CRNS for soil moisture measurement at four locations in northern Italy, concluding that CRNS significantly outperforms satellite-based methods. Morris et al. [39] showed that relatively simple corrections for vegetation biomass on the neutron signal were effective when compared to long-term historical data of neutron probes in Maize-Soybean sites. Zhang et al. [40] developed a method that employs a cosmic-ray neutron rover to measure soil moisture on the Tibetan Plateau and uses a data logger integrated into the control module to collect sensor data. Mazzoleni et al. [41] demonstrated the capability of CRNS to detect changes in soil moisture up to 25 cm deep due to sub-surface irrigation systems along grapevines. Al-Mashharawi et al. [42] explored the potential for CRNS to track water content in olive and cherry orchard pilot sites, demonstrating a good response when accounting for changes in vapor pressure deficit over time.

Work in [21] first explored the concept of irrigation management through neutron transport simulations, finding that statistical noise was a major limiting factor. The study, however, suggested that CRNS still offered potential for improvement in larger sites in arid regions with heavy irrigation requirements. Brogi et al. [18] showed through neutron transport simulations that whilst CRNS can be sensitive to irrigation, when applied to smaller fields (0.5-8 ha), variations in soil moisture in surrounding sites can also influence the signal. Further work in [19] subsequently demonstrated, in field trials, that CRNS could accurately detect changes in soil moisture due to irrigation in small plots, provided additional soil moisture measurements could be obtained on neighboring sites. For such a technique to be effective, however, additional tools are needed to automatically correct for differences in the shape and extent of irrigation areas. This highlighted the importance of building a strong understanding of contributing signals across a site, based on different irrigation zones, and of effectively integrating multiple distributed sensors across farming boundaries.

Cirillo et al. [43], working in a similar area, have examined the effects of farm operations on larger sites monitored by CRNS, demonstrating that changes in soil bulk density due to tillage can alter the correlation between CRNS and field conditions. This demonstrated the need for systems that can reliably map expected changes in farming operations to field observations to produce reliable data.

Despite the significant progress reported in the literature, existing work typically addresses only isolated aspects of the overall problem. Studies on CRNS primarily focus on sensing principles, calibration, and validation of soil moisture estimates, often relying on offline data collection or standalone data loggers, with limited discussion of IoT platforms, automated data pipelines, or long-term operational integration. Conversely, IoT platforms and smart irrigation systems reported in the literature generally rely on point-based soil moisture sensors or remote sensing products and do not natively support CRNS data products or their specific correction and calibration requirements. As summarized in Table 1, these research directions tend to address sensing, data management, and decision support in isolation, leaving the integration challenges associated with operationalizing CRNS data for automated irrigation management largely unaddressed.

In contrast, COSMIC-SWAMP integrates these previously separate research directions into an end-to-end IoT analytics platform, combining automated CRNS data ingestion and calibration, heterogeneous communication support, spatial and temporal data fusion into management-zone indicators, and forecasting-based decision support. This positioning highlights the contribution of the proposed platform not as a new sensing technology, but as an operational framework that enables the sustainable and scalable use of CRNS within smart irrigation systems.

III. SMART WATER MANAGEMENT PLATFORM (SWAMP)

The original Smart Water Management Platform [22] (SWAMP)[1] was designed to support smart irrigation by developing a robust IoT agricultural monitoring infrastructure that can interface with various environmental sensors. SWAMP combines arrays of in-field sensors, such as soil probes and irrigation monitors, and machine learning algorithms to perform data-driven irrigation scheduling [44]. SWAMP is built on the FIWARE open-source standard for smart applications, which provides a robust context broker (Orion) for storing data in MongoDB and time-series databases (QuantumLeap combined with CrateDB). The main advantage of SWAMP is its flexibility in supporting both large and diverse sensor networks, as well as modular processing algorithms based on a standardized NGSI contextual interface. This makes it possible to easily extend the platform to support new data processing routines or forecasting methods, whilst also allowing existing components to be replaced by other implementations in the future.

[1] https://swamp.pesquisa.ufabc.edu.br

TABLE 1. Qualitative comparison of representative approaches related to soil moisture sensing, IoT platforms for smart irrigation, and COSMIC-SWAMP.

Approach category	CRNS sensing	Automated calibration	IoT ingestion	Fusion / zones	Forecasting / DSS
CRNS and proximal sensing studies (e.g., Gaspar et al., 2025; Heistermann et al., 2023)	Yes	Partial / offline	Limited or offline	No	No
Remote sensing and UAV-based approaches (e.g., Díaz-Delgado et al., 2025)	No	Partial	Limited	Partial	No
Generic IoT smart irrigation platforms (e.g., ThingsBoard-based and similar systems)	No	N/A	Yes	Partial	Partial
COSMIC-SWAMP (this work)	Yes	Yes	Yes	Yes	Yes

The SWAMP model focuses on providing a common standard for exchanging information on irrigation scheduling. By dividing agricultural sites into numerous individual irrigation management zones, SWAMP aims to continuously monitor water demand within each zone, thereby optimizing total water application at a finer scale than would be possible with a manual approach. SWAMP developed their own multi-depth multi-parametric capacitive sensor probes for in-situ point measurements [45].

The major limitation of the original SWAMP platform is that it is explicitly optimized for arrays of in-situ capacitive probes to monitor each management zone. Since these probes are primarily used for point measurements within each zone, they may fail to capture soil moisture variation at larger scales. Consequently, large networks of them are necessary to monitor a collection of management zones. In-ground soil sensing systems also suffer from the fundamental limitation that they must be removed and reinstalled in the field during major farming operations. Since SWAMP relies on manual association of sensors with management zones, the sensors are physically placed in these zones, which imposes an additional requirement on farmers to update the mappings between sensors and individual zones whenever assets are physically moved on a farm. For an irrigation monitoring platform to be easily scalable to large farm sites and operationally viable for use over multiple growing cycles, it needs to effectively capture soil moisture neutrons so they are more likely to be absorbed before leaving the conditions, while accounting for potentially noisy/sporadic data expected in farming environments. In the following two sections, we review our proposed solutions to this need.

IV. COSMIC-RAY NEUTRON SENSING

The cosmic-ray neutron sensing technique offers a novel approach to non-invasively measuring soil moisture over large areas. A neutron detector placed above ground is sensitive to variations in local water content, which is caused by an increase in soil hydrogen, thereby moderating neutrons. Hence, they are more likely to be absorbed before leaving the soil. The correlation between neutron rate and Volumetric Water Content (VWC) is strongest in the epithermal energy range, between 1.0 eV and 0.1 MeV [46]. Cosmic ray neutron detectors are also sensitive to changes in local environmental conditions (pressure, absolute humidity, soil composition) and variations in the incoming primary cosmic ray flux. Whilst the former are typically obtained from co-deployed weather stations and soil calibration campaigns, the latter requires information from online sources, as discussed in detail in the subsequent section. Online processing algorithms are therefore necessary to correlate the observed neutron counting rate with VWC fully [13].

A common method used by several cosmic ray monitoring arrays involves calculating the fractional drop in observed neutron counts relative to an estimated maximum 'dry neutron counting rate' after correcting for background environmental variations. Given a neutron count rate from a sensor, the VWC is typically estimated as:

$$\theta_{\mathrm{VWC}} = \left(\frac{a_1}{f_p f_c \,(N/N_0) - a_2} - a_3 \right) \rho_d + \phi_{s'} \tag{1}$$

where N_0 is the expected counting rate for dry soils, f_p and f_c are correction factors for variations in local environmental conditions and incoming cosmic ray intensity respectively, ρ_d is the dry soil bulk density, and $\phi_{s'}$ represents additional constant contributions due to soil lattice water content and soil organic carbon [9]. The a_i terms are empirical factors that represent the correlation between the counting rate and water content, and are typically given by the following values: $(a_1, a_2, a_3) = (0.0869, 0.3720, 0.1236)$. f_p is typically derived from environmental data obtained from a weather station co-deployed with the cosmic ray station. f_c is typically derived from data obtained from the neutron monitor database [47], a network of high-energy cosmic ray monitors distributed globally around the world, which monitor the highest energy portion of the incoming cosmic ray intensity to estimate the flux before local environmental conditions modify it. This final correction influences are on the order of a few percent, which is significant given the sensitivity required for fine-scale irrigation monitoring and scheduling.

Whilst several global CRNS networks use this method to convert raw neutron counts to soil moisture, recent re-assessment of neutron behavior on field sites using detailed neutron transport simulations has shown that an alternative universal transport equation can give a more reliable estimate of soil moisture that properly accounts for neutron diffusion through humid air [48]. Despite this advancement in cosmic ray sensing, most existing users still rely on simpler correction functions, as in Equation (1), due to their ease of implementation. Several tools have recently been developed to support the adoption of new correction techniques.

However, these still require manual handling of text-file-based CRNS outputs after a data collection campaign, such as crspy [49] and CoRNy.[2] While older networks, such as the original COSMOS [15], demonstrated the ability to process data in real time as raw counts are transmitted over cellular or satellite connections, there have been few demonstrations of robust, flexible integration with other IoT devices for agricultural decision-making. The ADAPTER project is one of the most recent attempts at this, demonstrating the use of NB-IoT to automatically transfer data to a centralized server for providing daily site summaries to farmers [50]. It is clear that for the CRNS to achieve the level of precision required for precision irrigation, automated calibration procedures are necessary to account for local environmental conditions and to correct for the global cosmic-ray intensity obtained from the neutron monitor database. To date, no open-source framework exists that does not require continuous, extensive manual intervention by farmers to directly link soil moisture products from CRNS systems with irrigation systems and crop modeling tools.

In the next section, we discuss efforts to develop a set of extendable FIWARE Internet of Things software modules to address this challenge and support the broader use of IoT processing of cosmic ray data in an agricultural management context.

V. METHODOLOGY: THE COSMIC-SWAMP CONCEPT

COSMIC-SWAMP builds on lessons learned from the original SWAMP platform to develop a new sensor platform capable of supporting a wider range of soil sensors and responding to changing site conditions. This goal is achieved by transitioning to a geo-spatial referencing management approach, in which fields are subdivided into Management Zones. All relevant information for a zone, such as sensor data and agronomic plans, is dynamically linked to location attributes within the platform. Traditional in-situ soil moisture measurement methods in other networks [45] rely on probes at fixed locations, typically associating soil moisture monitoring data with irrigation platforms that are manually installed at sensor locations. Instead, the geospatial referencing considered in this work enables dynamic associations based on position, enabling irrigation routines to query sensors near a moving irrigation arm at a specific point in time to determine local soil moisture conditions. This approach results in a flexible framework that can automatically respond to changes in physical sensing systems, such as farmers relocating sensors during harvest, without requiring extensive manual intervention on the server management side for the farmer. Farmers must only upload the locations of their sensors and provide maps of their growing plans. Further simulation tools enable the platform to determine the most appropriate way to collate information for a specific management zone.

The overall structure of the COSMIC-SWAMP platform is illustrated in Fig. 1, which divides the platform into four key sub-platforms, each designed to operate as a self-contained unit. Each sub-platform is separated based on differences in processing procedures, and the resulting information is saved at each stage. The platforms are:

- IoT Platform: handles ingesting data from on-site devices and external data providers and transmitting control messages back to in-field devices.
- Information Platform: aims to standardize high-level data variables into the COSMIC-SWAMP data model (e.g., converting raw sensor readings to volumetric water content).
- Fusion and Forecasting Platform: handles management zone water content averaging and predicting future soil moisture on daily timescales for irrigation management.
- Simulation Platform: processing flow for predicting platform behavior at the sensor level over entire growing cycles based on simulated or historic data.

Aside from the core FIWARE modules used for contextual data storage in the original SWAMP platform (Orion, CrateDB, QuantumLeap), each COSMIC-SWAMP module is provided as a Python-based REST interface built with FastAPI [51], which provides automated documentation and robust input format checking. The COSMIC-SWAMP platforms are released under the GPL open-source license[3] in the hope that this will support a more robust ecosystem of processing tools in the cosmic ray sensing community, which could directly support farmers in the future.

A. IOT PLATFORM

The Internet-of-Things platform within COSMIC-SWAMP defines the backend components necessary for handling raw sensor data. This platform relies on core FIWARE modules to store current (MongoDB) and historical (CrateDB) contextual data, with the Orion Context Broker serving as a general management system for the current state of entities within the platform. Every property of interest on an agricultural site (from field extents to crop conditions and sensor locations) is represented as an NGSI-2-compliant entity in Orion, enabling the site's current state to be monitored. Furthermore, Orion's built-in service path capability is used in COSMIC-SWAMP to separate different agricultural sites (whether real or simulated), allowing a single platform deployment to be scaled across a wide range of field sites and operating configurations.

COSMIC-SWAMP uses LoRaWAN for wireless sensor data transmission and MQTT as an IoT data protocol. LoRaWAN is a distributed transmission technology operating in unlicensed ISM bands, currently at the forefront of the IoT smart applications, particularly in agriculture settings, as it

[2]https://git.ufz.de/CRNS/cornish_pasdy

[3]https://github.com/patrickstowell/COSMICSWAMP

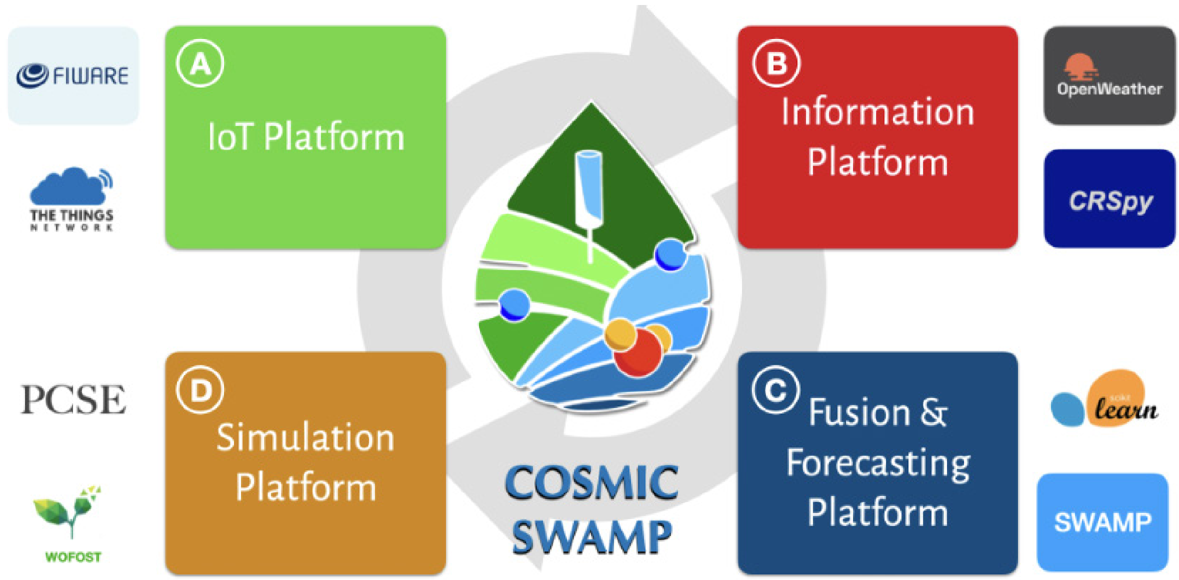

FIGURE 1. COSMIC-SWAMP Platform Overview. Raw sensor data arriving on the IoT Platform is parsed and sent to the Information Platform, which standardizes the data on key soil properties. Standardized data is used within the Fusion Platform to estimate the condition of each growing management zone and forecast future growth. Finally, historic data is used as an input in the Simulation Platform to predict future site behavior at the sensor level.

allows farmers to establish their own sensor networks that can automatically accommodate the installation of new devices. Since it operates on users' own network infrastructure, it offers high flexibility, adaptability, and efficiency. Yet, providing adequate Quality of Service (QoS) guarantees is challenging and depends on a careful understanding of different tradeoffs, such as sensor density, distance from the sensors to the gateway, and spreading factor [52].

MQTT provides a robust message transport protocol for collecting data from diverse sensor networks. MQTT provides three QoS levels to ensure reliable and robust communication, particularly in IoT applications [53]. By defining rules for message delivery, MQTT can adapt to varying network conditions and system requirements. QoS 0 prioritizes transmission speed and frequency over reliability, making it suitable for non-critical data transmitters that don't require delivery confirmation. QoS 1 ensures messages are delivered at least once, handling network issues but allowing duplicates. QoS 2 guarantees exactly-once delivery, preventing duplicates and data loss, making it ideal for critical applications.

COSMIC-SWAMP utilizes MQTT to retrieve sensor data from in-field devices. There is no standardized solution for processing incoming MQTT sensor data from different providers and ingesting it into the Orion Context Broker. Instead of running individual IoT agents for each possible sensor stream, COSMIC-SWAMP provides a generalized IoT agent that can be easily extended with simple Python-based parsing modules for each data format. These modules convert raw data into Next Generation Service Interface for Linked Data (NGSI)-compatible messages, ready to be ingested into Orion. The modular processing format allows libraries of typical message-format parsers to be added without the need to deploy a separate IoT agent for each type, or to require that all sensors deployed adopt a common message-format standard.

Weather stations connected to the platform regularly publish their data directly to the COSMIC-SWAMP servers using a 4G modem. When considering the deployment of large arrays of soil sensors, individual 4G modems per device do not scale well. Instead, several transfer solutions have historically been considered for smart farm field deployments, with LoRaWAN, a low-power wireless protocol, a common standard. Given its widespread use, LoRaWAN is considered a primary method for transmission from distributed in-field sensors. Several Internet-of-Things management services are available for testing remote device data transfer, such as The Things Network[4] or ChirpStack.[5] In the case of COSMIC-SWAMP, The Things Network (TTN) is the primary service provider, with test deployments considered in this work demonstrating the use of centralized 4G-enabled gateways that send data to TTN community servers before the platform queries them. The advantage of this approach is that a large array of publicly available gateways within the TTN network can be used for testing sensors within COSMIC-SWAMP across the globe in built-up areas. For deployments on remote farm sites, additional gateways can be installed and configured to transmit data to TTN, with multiple gateways potentially co-deployed across a farm site to provide large-area coverage or add redundancy in the event of a single gateway failure.

[4]https://www.thethingsnetwork.org
[5]https://www.chirpstack.io

An additional COSMIC-MQTT-bridge is necessary to allow sensor streams to be obtained both directly and from external service providers. This bridge subscribes to a user-provided list of data streams and publishes them to a local MQTT topic, allowing the platform to collate sensor data from many different MQTT sources into a centralized Orion context manager. For sensor streams, using external service providers, such as TTN, allows COSMIC-SWAMP to automatically subscribe to MQTT topics for all sensors deployed on the platform, thereby eliminating the need to configure each device to send data to a specific server endpoint hosting COSMIC-SWAMP. Since devices typically send data periodically within LoRaWAN, if the server or gateway experiences an intermittent failure, the data continues to be transmitted once the gateway-server connection is restored. Due to LoRaWAN message limitations, any data transmitted by sensors during this downtime is lost. However, this structure ensures that the entire sensor network is restored to a transmitting state once the servers are restored.

Fig. 3 illustrates the IoT Platform, highlighting the entire data flow from sensors to the Simulation Platform. This platform also enables the historical monitoring of raw data from all relevant data streams, including the CRNS probes designed for COSMIC-SWAMP and weather stations. It also exemplifies the MQTT data stream collation carried for a typical pilot. Unlike other readily available IoT agents, these modules are configured and monitored based on additional entities managed by Orion, making it easy to add different MQTT sources on a site-by-site basis if necessary. In addition to monitoring the current contextual state of each entity, the platform automatically saves the state of each time-varying entity in CrateDB after every update, using QuantumLeap as a generic enabler. This, combined with a Grafana-based monitoring system, enables the historical monitoring of raw information from all relevant data streams to assess the long-term stability of in-situ sensors.

B. INFORMATION PLATFORM

After collating raw sensor data and other contextual information, the COSMIC-SWAMP platform automatically processes it into NGSI format. When sensor data arrives on the platform, it can trigger a sensor-specific calibration service that uses the data to produce a final estimate of all parameters of interest necessary for understanding crop growth to date. For weather station data, this is simply the weather readings from in situ monitoring stations. In-field soil probes typically send raw data to the server, which then undergoes a secondary calibration step to produce a soil moisture reading.

The purpose of the information platform, depicted by Figure 3, is to collate available data sources necessary for calibration and output them in a standardized way. The output of this platform can therefore be considered ‘farmer-ready’ data, comprising real physical site variables (e.g., soil volumetric water content and its associated uncertainty, rainfall, temperature, pressure, and humidity). Similar to the IoT platform, the modules within the information platform are designed to interface with one another in a standardized way to support future extensions of calibration procedures. The roles of the IoT modules within the information platform are described individually below.

COSMIC-SWAMP API: The critical distinction between the original SWAMP platform and COSMIC-SWAMP at this stage is that each sensor reading must be assigned both a value and a location attribute, which defines a ‘validity footprint’ of that measurement within the site. This footprint accounts for changes in sensing area across different techniques, typically measured in centimeters for capacitive probes and in hundreds of meters for neutron probes. Additionally, a validity weighting parameter can be specified, which defines the falloff in sensitivity of the neutron sensing technique with increasing distance. This addition to the calibration procedure is relatively simple. Still, when combined with CrateDB’s and Orion’s geolocation capabilities, it enables efficient site-wide searching and averaging of measurements of interest. The COSMIC-SWAMP API facilitates querying data in this way by providing a singular interface that allows both current and historic entity states to be searched, as well as providing the ability to query based on spatial measurements, not devices (e.g., requesting all valid soil moisture measurements for a specific point in a field on a given date). Built as a FastAPI application, the COSMIC-SWAMP API also provides an accessible interface for higher-level site management through customizable Python scripts.

COSMIC-SWAMP Web Management: To support the transition to this new geospatial referencing model, a web management application is provided, which serves as a general entity editor tool for directly modifying all entities within a given site. In addition, the app provides a web-based service monitoring tool that interacts directly with the documentation and logging capabilities of each module, as well as a leaflet-based geospatial analysis tool for understanding how the sensitive footprints of each measurement intersect with potential site management zones.

Weather Forecaster: In addition to on-site weather data from weather stations, further data is required to forecast future crop growth and water needs based on weather forecasts. Several commercially available data sources are available through REST APIs for this purpose. One challenge with these sources is that not all APIs provide the exact information needed for crop growth estimation. The Weather Forecaster module aims to collate this available weather data and convert it into a common time-series format that includes current and future possible weather information, such as potential rainfall and environmental conditions (pressure, temperature, humidity, and incoming radiation). In cases where only limited information is available, such as 5-day forecasts, simple linear interpolation is used to produce hourly forecasts, which are associated with significant errors. This method enables the standardized handling of forecast data by modules outside the information platform.

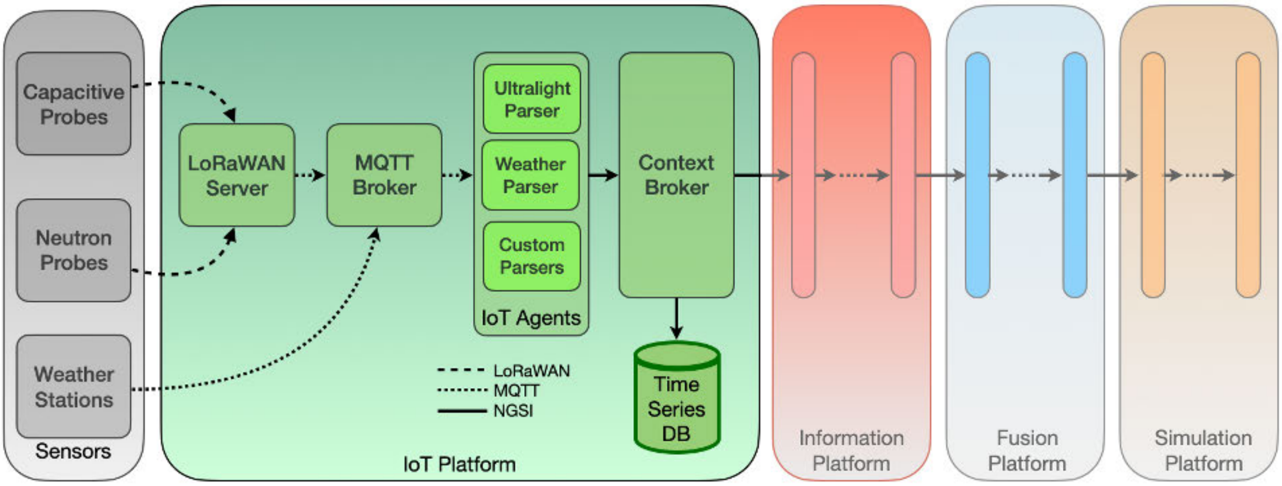

FIGURE 2. Multi-stream data collation using the COSMIC-SWAMP MQTT Bridge and Modular IoT Agent components. Raw data from both LoRaWAN-enabled capacitive probes and neutron sensors is combined with data from MQTT-enabled weather stations by a single context manager.

NMDB-Scheduler: Corrections are required to account for variations in incoming cosmic-ray intensity when aiming for measurement uncertainty below a few percent with the neutron sensing technique. Typically, data from either the Jungfraujoch neutron monitoring station in Switzerland is used to perform this correction [54]. However, some existing networks consider the nearest active neutron monitoring station available in the online neutron monitor database when making this correction [16]. The Neutron Monitoring Database (NMDB) enables querying cosmic-ray intensity variations for non-commercial purposes in near real-time via a REST API. To avoid overloading the NMDB interface with repeated queries for every device in COSMIC-SWAMP, the NMDB-Scheduler periodically queries data for each station relevant to the network and stores it in COSMIC-SWAMP as a NeutronDatabase contextual entity. This procedure enables data corrections to be applied using locally available data. It supports the possibility of adding local time-series measurements of cosmic ray intensity directly to the platform in the future (for example, by utilizing cosmic ray muon measurements [55].

Soil Probe Calibration: In the case of capacitive probes like those in SWAMP [45], [56], calibration is simply a soil-dependent correction function that relates the raw capacitive sensor reading in millivolts to soil moisture in volumetric water content $\%V/V$. These functions are typically obtained from calibration campaigns using soil samples from the deployment site in question to provide precise estimates. Whilst the capacitive probe only outputs a point reading in sensitivity, a location attribute is still assigned to the NGSI-calibrated sensor output. Importantly, the soil probe calibration service provides both forward and backward calibration functions, allowing not only soil moisture to be estimated from raw Analog-to-Digital Converter (ADC) values from the probe, but also a raw ADC value to be estimated for a given ground-truth soil moisture in simulated data.

CRSPY Server: Cosmic ray neutron probes require several correction steps to remove the influence of changes in local environmental conditions before the volumetric water content can be estimated (Section IV. The CRSPY server module in COSMIC-SWAMP takes advantage of community efforts to develop a standardized procedure for these corrections, providing a calibration micro-service that takes in relevant environmental data, raw neutron counting rate information, and estimates of dry soil neutron counts for a site and returns a corrected volumetric water content estimate with associated errors [49]. By default, the CRSPY Server module utilizes the standard corrections described by Bogena et al. [57]. Importantly, this separation of cosmic ray to volumetric water content corrections into its own component of the platform ensures that processing is always handled robustly and identically for each cosmic ray neutron probe, without requiring specialized knowledge of the corrections themselves. Additionally, a future extension to utilize more sophisticated cosmic-ray corrections, such as universal neutron transport methods [48], is straightforward.

CRNS Calibration: In contrast to capacitive probes, the CRNS technique requires a more complex calibration procedure that uses not only local weather data but also corrections for online cosmic ray flux measurements and knowledge of the soil composition at the site in question. Whilst this is a disadvantage for the technique compared to simpler probes, these corrections lend themselves well to automated processing routines. Typically, within a smart farm site, a number of these measurements will already be known and stored in the management platform due to other farm operations (for example, historic soil composition measurements or weather data from already-deployed in-situ weather stations).

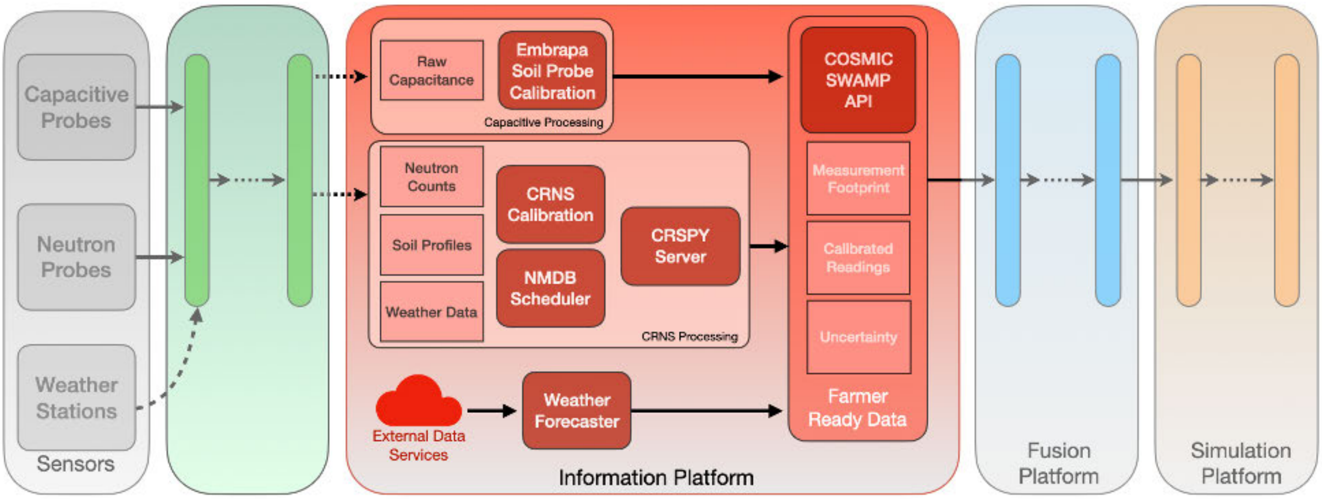

FIGURE 3. **COSMIC-SWAMP Information Platform Architecture. Raw sensor data streams are combined with dedicated calibration modules to convert them to farmer-ready data (e.g., volumetric water content). For CRNS processing, all steps required for the automatic conversion of sensor data are included in three modules: CRNS calibration, NMDB schedule, and CRSPY server interface.**

The CRNS Probe calibration module is designed to automatically query all relevant data from COSMIC-SWAMP for sensor calibration and then pass them to an external correction server for VWC calculation.

The query procedure is as follows:

1) CrateDB is queried for data on air temperature, pressure, and humidity within a 10 km radius, and the results are prioritized according to distance.
2) CrateDB is queried for site properties of interest, including soil composition and above-ground biomass estimates for all zones within the neutron probes' footprint.
3) CrateDB is queried for available incoming cosmic ray intensity data relevant to the site, defaulting to data from the Jungfraujoch monitor if no other preference is specified.
4) A standardized dataset from steps 1-3 is sent to the CRSPY Server package, which acts as an external correction server that returns an estimate of the VWC around a given sensor based on the provided data.
5) The converted soil moisture estimates are saved as new entity data in Orion and registered in the historical time-series databases.

Treating the VWC extraction with CRSPY as its own external package means that the soil moisture extraction routine could be easily updated in the future by replacing CRSPY Server with an alternative NGSI-compliant correction application. The geospatial query approach means that the COSMIC-SWAMP procedure for handling incoming cosmic ray data is implicitly fault-tolerant. Several neutron probes currently available come equipped with built-in environmental sensors. By default, a 300 m search radius is used to determine local soil properties and calibration data around a single probe, and a 1 km radius is used when querying weather station data near a probe. These search radii automatically expand to encompass the entire farm site if no valid data is obtained, allowing sensors to utilize redundant environmental data from other weather stations or even other sensors to perform corrections as needed.

The CRNS technique requires a calibration procedure to be performed that utilizes local field measurements of soil moisture using core samples or time-domain reflectometry (TDR) probes to estimate the dry neutron counting rate for a single probe (i.e., the N_0 parameter in Equation (1)). For hydrological field studies, this is typically done once after a calibration campaign during the probe's installation. To facilitate this, the CRNS calibration package is set up with an additional REST API interface that can be called to query all available local soil moisture measurements within a given spatial and temporal range (typically 300 m, as shown in Figure 4) and use this alongside the raw neutron counting rate to estimate the dry neutron counting rate for a given sensor. This is then saved directly into the entity for the device's attributes to be used in all future soil moisture readings. The automated handling of this data enables farmers to take soil moisture readings and record their locations without worrying about explicit data formatting or corrections using available processing tools. Whilst current commercial options that rely on satellite or 4G/5G for sensor data offer online correction services to end-users to extract VWC from raw soil moisture, the dry-counting rate still needs to be estimated. This calibration procedure aims to automate as much of the process as possible, allowing corrections to be handled locally on the COSMIC-SWAMP platform. Farmers are only required to provide field readings to the platform, thereby significantly simplifying the process. The processing flow for this calibration procedure is shown in Figure 4.

The result is that changes in local environmental conditions are fully accounted for, based on the correction functions in

Equation (1), automatically in the server back-end, with no manual intervention required by a novice user. Furthermore, the structure of the calibration modules enables the CRSPY server to be easily extended in the future to utilize more up-to-date correction functions without requiring manual implementation.

The combination of these rolling correction and calibration procedures results in completely automated handling of cosmic ray sensors in the field, eliminating the need for farmers to be experts in the CRNS technique to utilize their sensors effectively. The automated linking of manual soil moisture measurements to readings within a probe's footprint also enables farmers to directly correlate routine manual measurements with CRNS outputs, helping early adopters build trust in the sensing method before fully committing to its use in future irrigation decision-making. The availability of data from the information platform, compared to manual reprocessing methods, supports rapid decision-making based on sensor data, with the information being saved in a format that can be rapidly geo-queried to understand variability across an entire site. Compared with satellite-based monitoring schemes, which typically have 6-day response times for most accessible soil moisture products, this platform provides hourly response, with temporal variation over key weather events, such as rainfall or irrigation plans, observable at this resolution. Like the soil probe calibration case, the cosmic ray sensor calibration service also provides both forward and backward calibration methods, including statistical uncertainty in sensor counting rates during backward calibration. This enables the estimation of the effect that counting uncertainties may have on soil moisture estimation.

C. FUSION & FORECASTING PLATFORM

With soil sensor data standardized by the information platform, it is possible to efficiently calculate the most probable soil conditions for each management zone using all available data. The Fusion and Forecasting platform is designed to periodically assess the condition of each management zone. This assessment is based on data obtained from platform readings associated with geospatial footprints that intersect or fall within the boundaries of these zones. Therefore, the definition of each management zone is dictated purely by its location attribute. The advantage of this approach is that key property calculations are dynamic. If sensors are moved between zones after harvests or mounted to moving platforms (such as a rotating irrigation arm), the exact position and time of each measurement within Orion are available within the CrateDB historic database when estimating the state of a management zone at a particular time. When multiple property entities are available (for example, multiple sensors cover a single zone), a distance-weighted coverage estimate determines the zone condition based on all available data. The area of measurement that intersects the zone, after accounting for each sensor's maximal sensitive footprint, is calculated as w_i for each nearby sensor. These areas are then combined to weight a variable x_i in Equation (2).

$$x_w = \frac{\sum_i w_i x_i}{\sum_i w_i} \tag{2}$$

The spatial fusion expressed in Eq. (2) can be interpreted as a lightweight IoT analytics operation that aggregates heterogeneous sensor observations into management-zone soil moisture indicators. Rather than performing a simple arithmetic average, the fusion process integrates measurements from sensors with different sensing footprints through spatial weighting, enabling harmonization across heterogeneous soil sensing technologies. This transformation converts raw, sensor-level IoT data streams into stable, zone-level information suitable for automated irrigation decision support.

Every day, the DataFusion module is set up to perform this calculation of all parameters of interest x_w for every management zone within the platform, so that a state array containing both the current key growing properties and all relevant historic properties since the start of the current growing period is available for carrying out forecasting tasks for each zone.

Given the historical evolution of specific management zones, it is possible to infer the current crop condition by passing this data into simulations of the specific crop in question. COSMIC-SWAMP uses the Python Crop Simulator Environment (van Diepen et al.), which employs WOFOST [58] crop simulation models and daily environmental data to estimate plant growth over time. The PCSE model considers soil conditions, crop type, sowing dates, and environmental conditions as inputs, enabling daily-resolution predictions of plant growth.

COSMIC-SWAMP uses PCSE (The Python Crop Simulation Environment) [59] in a similar fashion to how it is used within the original SWAMP platform [60] but extends the interface to include the use of Kalman Filtering to both infer and forecast unobservable crop parameters such as crop root size using historic observables based on similar assimilation methods demonstrated with the PCSE framework [61]. In this method, a series of simulation ensembles is generated based on prior knowledge of the field site. Each ensemble is simulated with a time step of one day, after which its soil moisture predictions are compared to real data within the platform. Differences between ensemble predictions and real data are used to estimate shifts in ensemble parameters, thereby aligning the model predictions with the real data until the model converges on the current estimated field state, given all available field data and prior knowledge. The spread across predictions from all ensembles then provides an estimate of the model's uncertainty. In addition to estimating the current state, the forecasting tool uses PCSE to estimate several baseline irrigation scenarios — no future irrigation, minimal, and maximal — which can be defined by the farmer based on estimated maximum inputs requested and their previous growing-season experience. Since PCSE predicts crop growth performance, this estimates potential

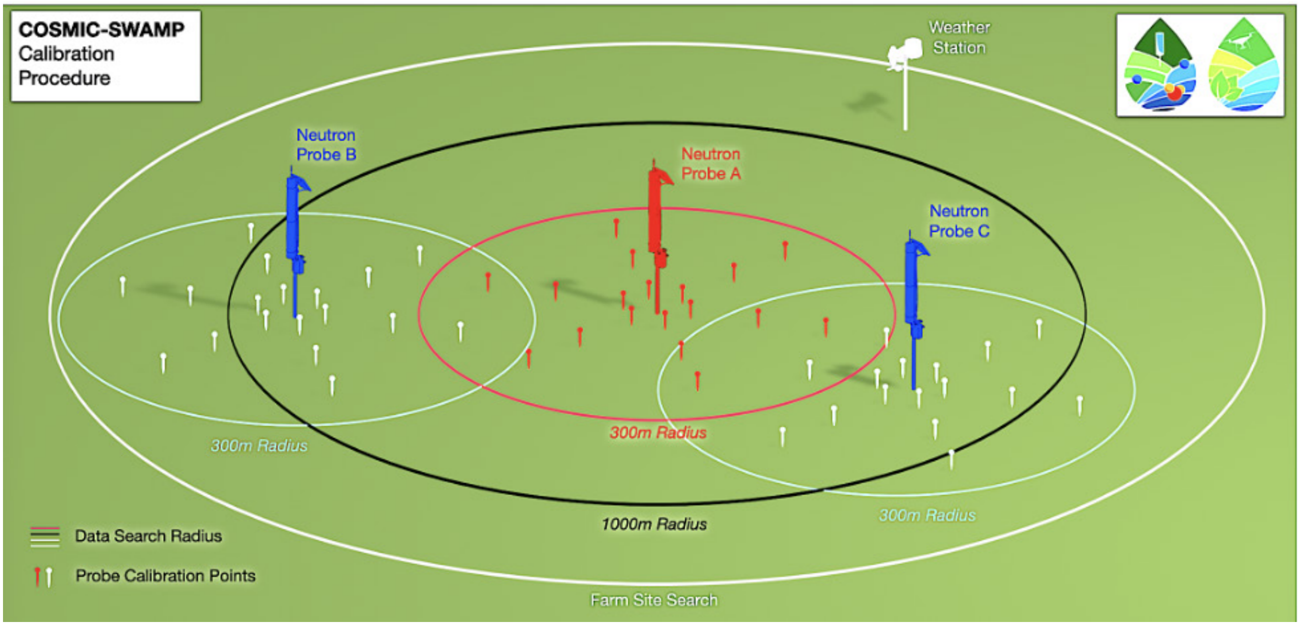

FIGURE 4. CRNS calibration data search procedure used within COSMIC-SWAMP. Probe calibration measurements are queried by their exact location, allowing sensors to use neighboring sensors' calibration points if they were taken within the calibration period. Weather station data is obtained using a distance-weighted query that can also use environmental sensor data from neighboring probes if available.

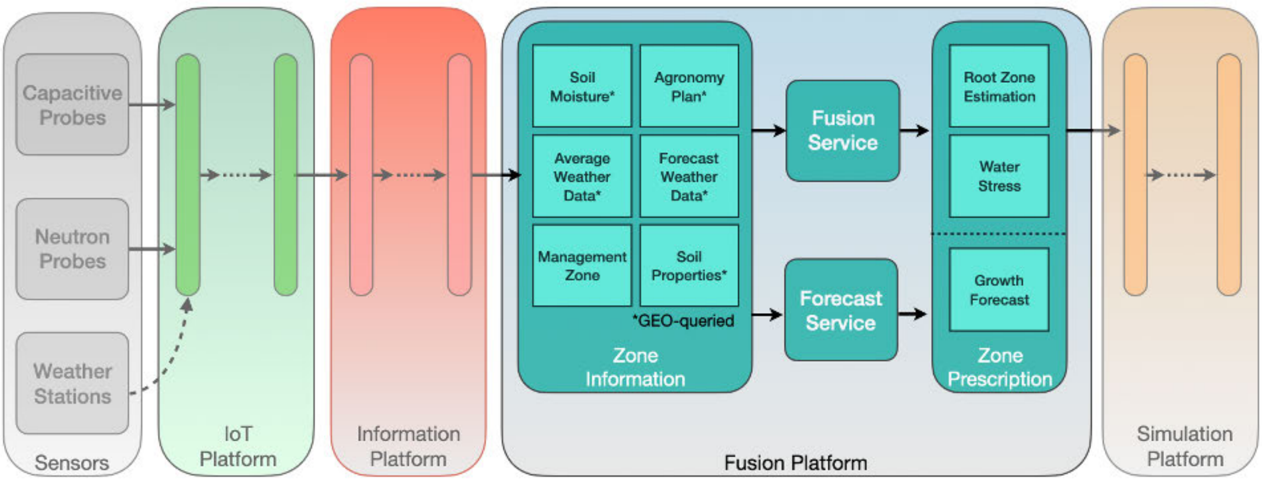

FIGURE 5. Fusion Platform Architecture. Historical management zone information, including soil and weather conditions and crop plans, is combined to estimate the current state of crops in the zone. Querying of zone-relevant data is based solely on the zone's spatial characteristics. Fusion and Forecasting are achieved by performing a data-driven simulation using PCSE.

yield differences under configurable irrigation scenarios. The prior Kalman filtering approach provides an updated starting point for each ensemble in the crop model data for a particular site, which can then be used to simulate the future evolution to the end of the growing cycle based solely on available weather forecast data. While the outputs are highly dependent on weather forecast uncertainties, this provides a comprehensive example of crop forecasting within the IoT platform, enabling users to explore the future evolution of crop growth in the current cycle across various agronomic scenarios.

Within COSMIC-SWAMP, the Fusion and Forecasting platform implements a chain of IoT analytics functions that operate across heterogeneous soil moisture sensing technologies. The fusion stage performs a lightweight spatial analytics that aggregates sensor-level measurements with different sensing footprints into zone-level soil.

D. SIMULATION PLATFORM

COSMIC-SWAMP includes a simulation platform that provides an independent tool for evaluating its performance across a diverse range of crop-growing scenarios. The platform provides tools to support in situ simulations of the entire site for evaluating the performance of a potential sensor array. Furthermore, the forward and backward calibration functionality of the information platform enables PCSE to simulate the platform's response at the sensor level, allowing every platform component to be validated and benchmarked through simulations. COSMIC-SWAMP loads all historical data for each zone from the current time to the start of the growing period for the given zone, simultaneously estimating the current soil moisture and root size.

One major challenge in adopting data-driven irrigation systems is assessing the impact of the updated prescription on future crop growth. Currently, there is no straightforward way to feed data directly into crop modeling platforms, and farmers typically need to collect and format data for specific models manually. When considering irrigation zones with differing inputs, these need to be manually updated on a zone-by-zone basis, making it difficult to rapidly see how different prescriptions could optimize growth on a site-wide basis. When considering future sensor deployments, it is also important to consider the trade-off between sensor resolution and cost, as well as the impact multiple sensors can have on reducing forecasting uncertainty.

The simulation platform in COSMIC-SWAMP attempts to leverage the fact that, after information and fusion platform processing, historical data across an entire site is available to a farmer. This data can be used as inputs to crop growing models to first validate the reliability of a model to predict key performance metrics at specific dates from other readings, such as leaf area index or total yield at harvest, before also being used to simulate future growth performance under a variety of different site conditions, such as irrigation prescriptions. In COSMIC-SWAMP, this simulation stack goes beyond simple end-level variable simulations (such as soil moisture). Instead, it uses a backward calibration model to simulate raw sensor-level inputs, thereby mimicking how they would behave when inserted into the platform at the IoT stage. While increasing computational complexity, this approach allows simulations to be performed across the entire network, enabling an understanding of how specific choices of sensor locations or sensor resolution affect the platform's ability to set constraints on soil moisture in specific irrigation zones.

Several studies have examined the resolution required for cosmic-ray sensing in irrigation prescriptions. This setup enables understanding of these limitations on multi-sensor arrays by running simulations with varying irrigation levels and examining their impact on water-stress resolution and future forecasting outputs. For this to be reliable, the backward calibration model must include detector smearing effects, such as those arising from ADC resolution or calibration uncertainty in point capacitive probes [62], [63], or from overall counting-rate uncertainty in cosmic-ray neutron sensors.

The procedure that allows for this sensor-level site simulation is as follows:

1) Starting crop conditions and soil properties are taken for each management zone within a given site.
2) Environmental data is estimated for the site over the entire growing period using an available weather source.
3) The PCSE interface produces a time-series estimate of soil moisture evolution for each zone.
4) For each sensor in the site, a 'local soil condition' is calculated based on a weighted average of all management zones that intersect its sensitive footprint location attribute.
5) The sensor's average 'local soil condition' is backward calibrated to produce a raw sensor reading for each simulation time (e.g., millivolts for capacitive probes, raw neutron counts for neutron sensors).
6) Steps 4–5 are repeated for all possible sensors at the site.
7) The weather data and collection of raw sensor data are organized as a long time-series ordered data frame, which contains updated values for each entity.
8) The raw data is uploaded in series to the Orion context broker, moving through the list of possible uploaded data.
9) The COSMIC-SWAMP platform's notification system is left to handle the automated processing and calibration of the raw data as if it were real data, including forward calibration and soil moisture extraction.

This procedure allows a soil moisture estimate for each zone to be requested at the end, enabling an understanding of the relative difference between the truth simulation input and the COSMIC-SWAMP output. An example of using this end-to-end simulation chain is shown in Figure 4. A simulation of one irrigation zone in a COSMIC SWAMP pilot is shown with a simplified deployment consideration of one neutron probe and one capacitive soil probe co-deployed. For weather inputs, it is possible to use historical data from either the ECMWF's ERA5-Land database[6] or the NASA POWER databases[7] for a chosen simulated deployment site. Soil moisture in the zone is estimated daily using two different irrigation prescriptions. The data is used with the backward calibration service to predict raw sensor counts, which are then passed to the COSMIC SWAMP platform as if it was real data. The insertion of this data triggers an automatic correction (information platform) and averaging (fusion platform) for the simulated day, resulting in a final estimate of soil moisture and site conditions. This can then be compared with the proper soil moisture to provide an estimate of overall uncertainty and the sensors' response to the irrigation change. In this scenario, the uncertainty from both probes is roughly 2-3% when averaged over a daily timescale. Importantly, the simulation properly captures the increased uncertainty in soil moisture during wetter periods for cosmic-ray neutron sensing.

The major impact this soil moisture simulation tool has on end users is that it provides a template for directly integrating soil moisture products from the fusion platform into site-wide simulations, allowing diverse deployment scenarios to be

[6]https://www.ecmwf.int/en/era5-land
[7]https://power.larc.nasa.gov

understood by more expert users before purchasing additional sensors.

VI. EVALUATION METHODOLOGY AND RESULTS

We evaluated the behavior of the COSMIC-SWAMP platform using initial test deployments and simulation scenarios.

A. METHODOLOGY

The evaluation of the COSMIC-SWAMP platform focuses primarily on a quantitative assessment of its IoT analytics capabilities for smart irrigation, complemented by a qualitative analysis of system flexibility under real deployment conditions. Quantitative metrics are used to evaluate calibration accuracy, temporal aggregation, spatial data fusion, and uncertainty behavior across heterogeneous soil moisture sensors, while qualitative observations highlight the platform's ability to operate robustly in dynamic IoT environments.

To evaluate the suitability of the COSMIC-SWAMP platform for in-field monitoring, a set of prototype LoRaWAN-connected cosmic-ray neutron probes was deployed at the Sheepdrove Farm (UK), an operational agricultural site equipped with an established reference sensor. The deployment was conducted in close proximity to a CRS1000/B cosmic-ray neutron sensor (Hydroinnova), which served as a baseline for comparative analysis [64]. The prototype sensors, developed at the University of Durham, employ boron-nitride-based scintillator detectors and are denoted BNCS1, BNCS2, and BNCS3 (Boron Nitride Cosmic Sensors, BNCS). In these systems, neutron interactions produce scintillation pulses that are discriminated from background signals using timing-based electronic thresholds. In contrast, the CRS1000/B relies on a boron trifluoride gas detector and represents a widely used commercial sensor system in cosmic-ray neutron sensing networks. Scintillator-based platforms [65], such as the BNCS, are considered a cost-efficient alternative to gaseous proportional counters based on helium-3 or boron-10 [66]. Both sensing systems provide hourly-integrated cosmic-ray neutron counts together with local measurements of pressure, temperature, and humidity.

The BNCS systems transmitted data to the COSMIC-SWAMP platform using a full LoRaWAN communication stack, while the co-located CRS1000/B (Hydroinnova) sensor transferred data to an external web server via an Iridium satellite modem. Data from the Hydroinnova system were periodically retrieved by the COSMIC-SWAMP platform through a custom MQTT-based ingestion agent. The simultaneous operation of these heterogeneous communication and data acquisition paths enabled an evaluation of the COSMIC-SWAMP information and fusion platforms, assessing their ability to automatically ingest, standardize, and process soil-moisture-related data streams originating from distinct sensor technologies and network infrastructures.

The three BNCS sensors were operated continuously for a period of approximately three months to compare volumetric water content (VWC) estimates produced by the COSMIC-SWAMP platform against those obtained from the co-located CRS1000/B reference system. Each prototype device was registered within COSMIC-SWAMP as an independent entity, denoted BNCS1, BNCS2, and BNCS3. Sensor-specific calibration was performed automatically by the COSMIC-SWAMP calibration service, which estimated the raw neutron counting rate parameters for each BNCS device using data from the nearby Hydroinnova sensor as a reference. During the deployment, a malfunction in the onboard temperature compensation of the BNCS1 probe resulted in an incomplete dataset for that sensor. Nevertheless, over the full deployment period, raw data from all available sensors were automatically ingested, calibrated, and processed through the complete COSMIC-SWAMP pipeline to generate soil moisture estimates. Measurements of atmospheric humidity provided by the Durham neutron probes were used to correct environmental effects in the neutron count data for both sensing systems. Owing to the use of an Iridium satellite link, data from the CRS1000/B system were retrieved and incorporated into COSMIC-SWAMP at approximately biweekly intervals following the initial data acquisition period.

Table 2 summarizes the quantitative metrics adopted to evaluate the IoT analytics capabilities of the COSMIC-SWAMP platform.

B. IoT AND INFORMATION PLATFORMS

Figure 8 shows the strong correlation between the water content extracted directly from the CRS1000/B probe and the Durham scintillator sensors added to the COSMIC-SWAMP platform. Unfortunately, a failure in the LoRaWAN gateway connectivity due to issues with the 4G service provider resulted in several weeks of missing data. Whilst the boron-based sensors include a queue system to support short network outages, extended outages lasting for long periods resulted in lost data. The extracted soil moisture estimate from COSMIC-SWAMP was consistent with that obtained from the CRS1000/B within 5-10% VWC. The raw counting rate of the BNCS systems was found to be between 48% and 56% of the CRS1000/B system. However, all three functioning systems showed a relative shift in neutron count rates over time. Some diurnal variation was observed on the prototype BN systems relative to the CRS1000/B tube, with the highest fluctuations occurring in BNCS2. This was believed to be due to an incorrectly set trigger threshold on the BNCS2 system, making it overly sensitive to the temperature drift of low-level photomultiplier tube signals. Despite this, the daily-averaged extracted soil moisture (Figure 7, bottom plot) agreed at the few percentage level for BNCS1 and BNCS3, with correlation coefficients greater than 70%, as shown in Figure 8.

Due to issues with LoRaWAN gateways, several data breaks are shown in Figure 4. It is clear, however, that because the cosmic-ray sensing correction methods rely solely on current environmental data, the measured soil moisture from

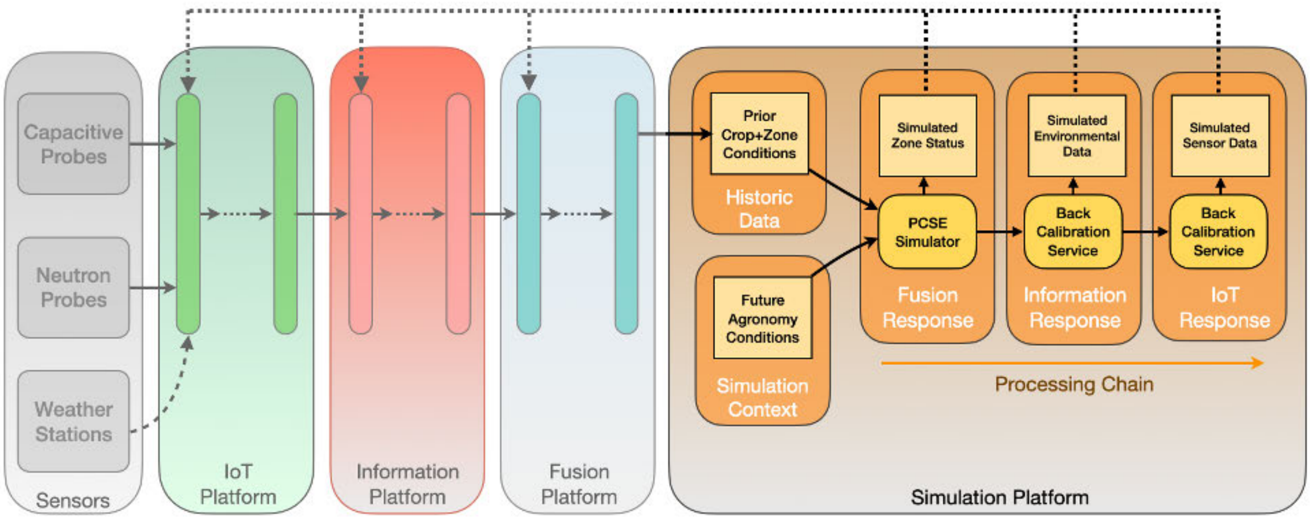

FIGURE 6. **Simulation Platform: Historical data or newly generated simulation contexts can be used as inputs to the PCSE simulator, which can be used to predict the crop and soil conditions of a specific zone in the network. Back calibration services can then be used to predict simulated environmental data or even raw sensor data for testing the response of the entire platform.**

TABLE 2. **Summary of evaluation metrics used in the quantitative analysis.**

Metric	Unit	Definition
Volumetric Water Content (VWC)	% (v/v)	Estimated soil moisture expressed as volumetric water content derived from calibrated cosmic-ray neutron count data.
Pearson correlation coefficient (r)	–	Linear correlation between VWC estimates obtained from BNCS sensors and the CRS1000/B reference system.
Root Mean Square Error (RMSE)	% (VWC)	Square root of the mean squared difference between BNCS-derived and reference VWC estimates.
Mean Bias Error (Bias)	% (VWC)	Average signed difference between BNCS-derived and reference VWC values, indicating systematic offset.
Standard deviation (σ)	% (VWC)	Statistical dispersion of VWC estimates over time, used to characterize measurement noise and temporal variability.
Neutron count rate ratio (N/N_0)	–	Ratio between measured neutron count rates and dry reference count rates used for soil moisture retrieval.
Uncertainty propagation	% (VWC)	Variation in VWC estimates arising from sensor noise and model uncertainty in simulated irrigation scenarios.

the working probes was consistent with data obtained from the CRS1000/B system each time the LoRaWAN gateway was restored. The one exception to this is the BNCS2 system, due to its strong temperature response, which highlights the potential issue that faulty probes can pose to the network's ability to estimate current soil moisture.

C. FUSION AND SIMULATION PLATFORMS

The simulation platform enables understanding of how key fundamental limitations of different sensors, such as the increase in relative uncertainty at high soil moisture for cosmic ray probes, can influence the platform's responsiveness to various rainfall or irrigation events. Figure 9 shows a PCSE simulation of sorghum growth at a water-limited site in Brazil used to predict the change in calibrated soil moisture readings (after the backward and forward calibration steps) for both simulated capacitive depth probes and a simulated neutron probe under two different irrigation scenarios. The neutron probe in question has an estimated dry counting rate of 2000 counts per second. Figure 9 reveals that, in general, the neutron probe can observe the same daily shifts in soil moisture as the capacitive probes but has higher relative uncertainty on hourly readings in the periods immediately after irrigation due to higher statistical noise when soil moisture is higher. While only a prototype, this demonstrates COSMIC-SWAMP's capability to support a fully end-to-end simulation of site response to changing irrigation conditions during a growing season, capturing the inherent uncertainty of specific sensor types implemented on the platform itself.

D. IoT ANALYTICS AND STATISTICAL EVALUATION

A quantitative assessment of soil moisture estimation is essential to validate the effectiveness of IoT-based analytics and automated calibration pipelines in real-world deployments. In the context of cosmic-ray neutron sensing (CRNS), such evaluation must also account for the statistical nature of neutron counting processes and the impact of temporal aggregation on measurement stability. Within the COSMIC-SWAMP platform, IoT analytics are employed to process, calibrate, and harmonize heterogeneous CRNS data streams, enabling a consistent comparison across different sensing technologies.

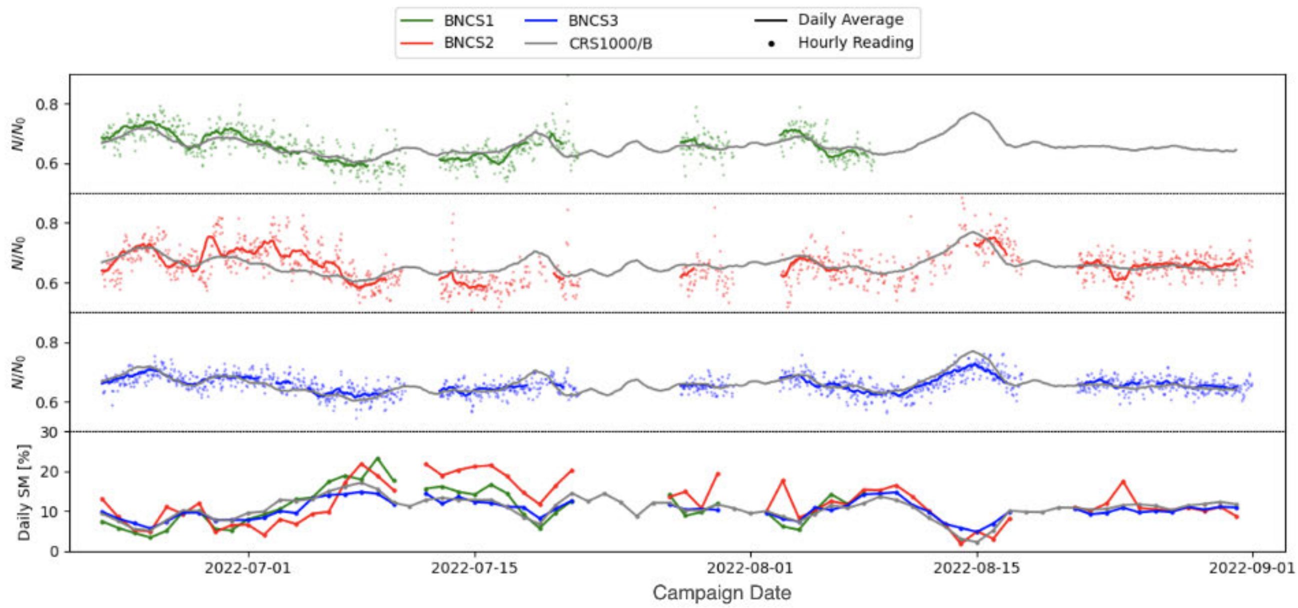

FIGURE 7. Data from the UK Sheepdrove pilot study for COSMIC-SWAMP. "BNCS" corresponds to the three COSMIC-SWAMP Boron Nitride probes deployed. Raw sensor data was transmitted via LoRaWAN to the central COSMIC-SWAMP server. The top three plots show the uncorrected ratio from Equation 1. Further processing, corrected for pressure and humidity, is shown at the bottom, along with Soil Moisture (SM) estimates. Breaks in the BNCS data correspond to server downtime during COSMIC-SWAMP development.

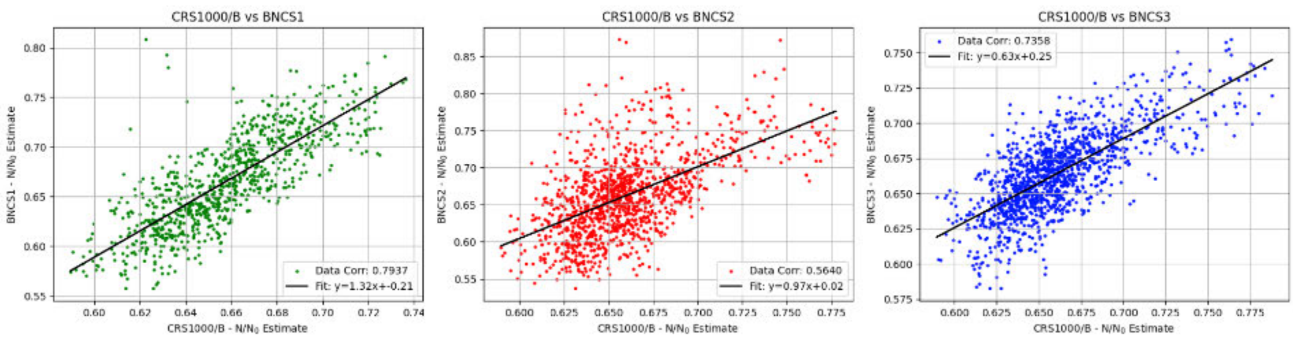

FIGURE 8. Correlation coefficients for the alternative BNCS cosmic ray sensor probes compared to the Hydroinnova system. BNCS1 and BNCS show a stronger correlation with the CRS1000/B system than BNCS2 due to the inherent noise issues discussed with BNCS2.

Table 3 summarizes the statistical performance of the boron-nitride-based cosmic-ray neutron sensors (BNCS) after automated calibration within the COSMIC-SWAMP platform, using the co-located CRS1000/B sensor as a reference, considering a 6-hour integration window. The reported metrics include the Pearson correlation coefficient (r), root mean square error (RMSE), mean bias, and standard deviation of the volumetric water content (VWC) estimates. Overall, BNCS1 and BNCS3 exhibit strong correlation and low bias with respect to the reference system, indicating that the COSMIC-SWAMP calibration and processing pipeline is able to produce consistent soil moisture estimates from heterogeneous CRNS technologies. In contrast, BNCS2 shows reduced performance, which is consistent with the hardware-related temperature sensitivity observed during the deployment. It is important to note that cosmic-ray neutron sensing is inherently a counting experiment; therefore, shorter integration windows tend to increase statistical noise, leading to lower correlation values between sensors. These results demonstrate that the platform's IoT analytics can both harmonize measurements across different sensing technologies and expose sensor-specific anomalies, thereby supporting robust soil moisture estimation in real-world deployments.

VII. DISCUSSION

The results presented in this study should be interpreted in light of the system-oriented scope of the work, which focuses on the operational integration of cosmic-ray neutron sensing (CRNS) within an IoT-based smart irrigation platform. Rather than aiming at an exhaustive metrological evaluation of soil moisture sensing technologies, the proposed approach emphasizes automated data ingestion, calibration, fusion, and analytics under real deployment conditions.

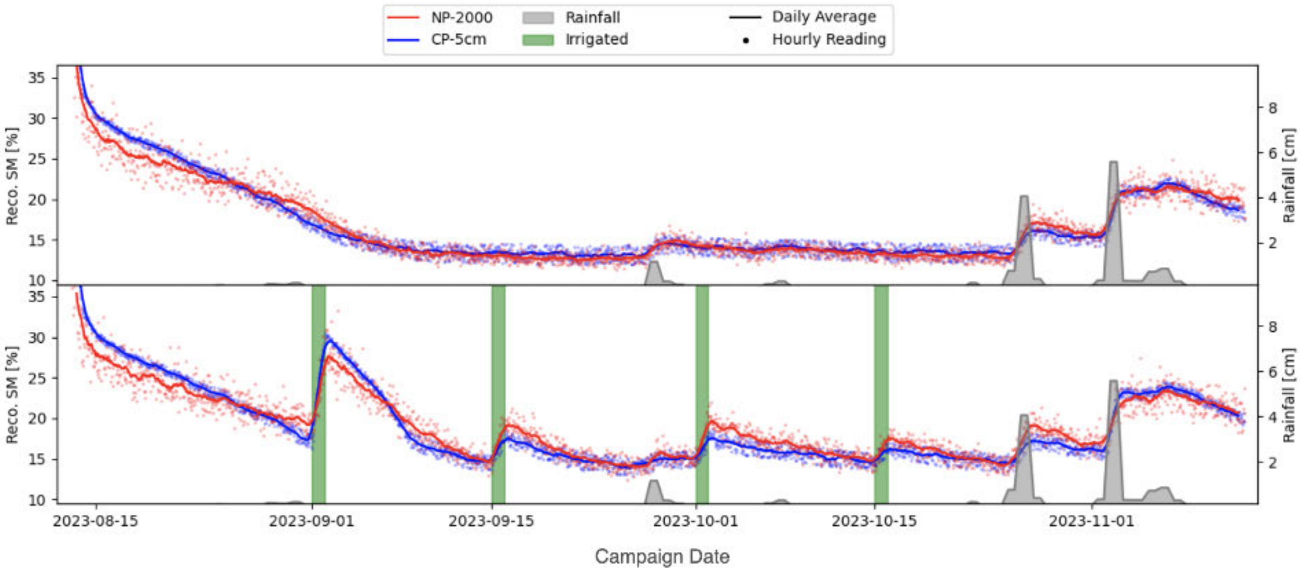

FIGURE 9. Simulation of raw sensor response to changing soil conditions under different sorghum growing scenarios in COSMIC-SWAMP. The sowing date is assumed to be August 15, 2023. PCSE estimates soil moisture evolution in each zone over time, given crop growing conditions and gridded weather data, before COSMIC-SWAMP calibration routines predict raw sensor data and reconstruct Soil Moisture (SM) from the readings. In the top plots, the sensor response for a water-limited case is shown; in the bottom plots, the sensor response for a case with timed irrigation events is shown using green vertical lines.

The evaluation demonstrates that COSMIC-SWAMP is capable of harmonizing heterogeneous soil moisture data streams originating from different CRNS devices and communication infrastructures, transforming raw sensor observations into management-zone-level indicators suitable for irrigation decision support. The consistency observed between prototype BNCS sensors and a commercial reference system indicates that the platform's calibration and analytics pipeline can support the operational use of CRNS data despite hardware heterogeneity and data acquisition constraints.

TABLE 3. Statistical performance of CRNS probes over a 6 hour integration windows after COSMIC-SWAMP calibration (RMSE, Mean Bias and Std. Dev. are given in %VWC.

Sensor	Corr. (r)	RMSE	Mean Bias	Std. Dev.
BNCS1	0.836	3.16	0.24	5.20
BNCS2	0.573	5.06	1.14	6.00
BNCS3	0.770	2.08	-0.17	2.87

Several sources of uncertainty and limitation must nevertheless be acknowledged. A first source of uncertainty arises from the statistical nature of cosmic-ray neutron measurements, where counting noise can introduce variability in short-term soil moisture estimates. While temporal aggregation mitigates part of this effect, residual fluctuations remain, particularly under low neutron flux conditions. Environmental corrections related to atmospheric pressure, humidity, and vegetation biomass further contribute to uncertainty, despite the application of established correction models.

Spatial heterogeneity within the effective CRNS footprint represents another important factor. In agricultural fields with non-uniform soil properties or irrigation patterns, the large sensing footprint of CRNS integrates multiple soil conditions, which may differ from point-based reference measurements. This scale mismatch is inherent when comparing field-scale sensing approaches with localized in-ground sensors and should be considered when interpreting quantitative error metrics.

Hardware-related factors also influence data quality and reliability. During the deployment, one of the prototype BNCS sensors exhibited temperature-related issues that resulted in incomplete data, highlighting the importance of robust sensor design and continuous monitoring in long-term deployments. In addition, operational constraints associated with heterogeneous communication technologies, such as latency and intermittent data availability (e.g., satellite-based data transfer), can affect the timeliness of analytics outputs, although they do not compromise the integrity of the underlying measurements.

From an IoT analytics perspective, these limitations underscore the importance of integrated platforms that explicitly manage uncertainty, heterogeneity, and data provenance. The Fusion and Forecasting components of COSMIC-SWAMP exemplify how spatially weighted data fusion and model-based forecasting can transform heterogeneous sensor data into decision-ready information, while maintaining traceability of assumptions and limitations. By making uncertainties and data gaps explicit at the platform level, such approaches support more informed irrigation management decisions.

Overall, the discussion highlights that the observed errors and variability are consistent with known characteristics of CRNS-based sensing and heterogeneous IoT deployments. The validation provided in this work is therefore best understood as a system-level proof of concept, demonstrating feasibility, interoperability, and automated operation. These findings motivate future work focused on extended measurement campaigns, deeper metrological validation, and uncertainty-aware analytics, which are outlined in the concluding section.

VIII. CONCLUSION

This paper presented COSMIC-SWAMP, an end-to-end IoT analytics platform designed to operationalize cosmic-ray neutron sensing (CRNS) data for smart irrigation systems. The proposed solution addresses the challenge of integrating heterogeneous sensing technologies, communication infrastructures, and analytics workflows into a unified platform capable of supporting automated irrigation decision support.

A real-world deployment involving prototype and commercial CRNS sensors was used as a proof of concept to demonstrate the feasibility of automated data ingestion, calibration, fusion, and analysis under operational conditions. The results show that the platform can harmonize heterogeneous soil moisture data streams, generate consistent volumetric water content estimates, and support zone-based analytics within the scope of a system-oriented evaluation.

Future work will focus on extended measurement campaigns across different crops and climatic conditions to enable deeper metrological validation, as well as on the integration of uncertainty-aware analytics and adaptive decision-support strategies. These efforts will further strengthen the role of CRNS-enabled IoT platforms in sustainable and scalable irrigation management.

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REFERENCES

[1] A. A. Abdelmoneim, H. N. Kimaita, C. M. Al Kalaany, B. Derardja, G. Dragonetti, and R. Khadra, "IoT sensing for advanced irrigation management: A systematic review of trends, challenges, and future prospects," *Sensors*, vol. 25, no. 7, p. 2291, Apr. 2025, doi: 10.3390/s25072291.

[2] A. Ali, T. Hussain, and A. Zahid, "Smart irrigation technologies and prospects for enhancing water use efficiency for sustainable agriculture," *AgriEngineering*, vol. 7, no. 4, p. 106, Apr. 2025, doi: 10.3390/agriengineering7040106.

[3] G. Saha, F. Shahrin, F. H. Khan, M. M. Meshkat, and A. A. M. Azad, "Smart IoT-driven precision agriculture: Land mapping, crop prediction, and irrigation system," *PLoS ONE*, vol. 20, no. 3, Mar. 2025, Art. no. e0319268, doi: 10.1371/journal.pone.0319268.

[4] X. Zhang, G. Feng, and X. Sun, "Advanced technologies of soil moisture monitoring in precision agriculture: A review," *J. Agricult. Food Res.*, vol. 18, Dec. 2024, Art. no. 101473, doi: 10.1016/j.jafr.2024.101594.

[5] M. W. Rasheed, J. Tang, A. Sarwar, S. Shah, N. Saddique, M. U. Khan, M. I. Khan, S. Nawaz, R. R. Shamshiri, M. Aziz, and M. Sultan, "Soil moisture measuring techniques and factors affecting the moisture dynamics: A comprehensive review," *Sustainability*, vol. 14, no. 18, p. 11538, Sep. 2022, doi: 10.3390/su141811538.

[6] J. Peng et al., "A roadmap for high-resolution satellite soil moisture applications – confronting product characteristics with user requirements," *Remote Sens. Environ.*, vol. 252, Jan. 2021, Art. no. 112162, doi: 10.1016/j.rse.2020.112162.

[7] T. Foster, T. Mieno, and N. Brozović, "Satellite-based monitoring of irrigation water use: Assessing measurement errors and their implications for agricultural water management policy," *Water Resour. Res.*, vol. 56, no. 11, p. 2020, Nov. 2020.

[8] M. Köhli, "Soil moisture measurements by cosmic-ray neutron sensing: A critical review," *Geoderma*, vol. 465, Jan. 2026, Art. no. 117626. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0016706125004677

[9] M. Zreda, D. Desilets, T. P. A. Ferré, and R. L. Scott, "Measuring soil moisture content non-invasively at intermediate spatial scale using cosmic-ray neutrons," *Geophys. Res. Lett.*, vol. 35, no. 21, p. 21402, Nov. 2008. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1029/2008GL035655/abstract

[10] S. Mollerach and E. Roulet, "Progress in high-energy cosmic ray physics," *Prog. Part. Nucl. Phys.*, vol. 98, pp. 85–118, Jan. 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0146641017300881

[11] M. R. Iyer and A. K. Ganguly, "Neutron evaporation and energy distribution in individual fission fragments," *Phys. Rev. C*, vol. 5, no. 4, pp. 1410–1421, Apr. 1972. [Online]. Available: https://journals.aps.org/prc/abstract/10.1103/PhysRevC.5.1410

[12] D. Desilets, M. Zreda, and T. P. A. Ferré, "Nature's neutron probe: Land surface hydrology at an elusive scale with cosmic rays," *Water Resour. Res.*, vol. 46, no. 11, p. 11505, Nov. 2010. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1029/2009WR008726/pdf

[13] M. Köhli, M. Schrön, M. Zreda, U. Schmidt, P. Dietrich, and S. Zacharias, "Footprint characteristics revised for field-scale soil moisture monitoring with cosmic-ray neutrons," *Water Resour. Res.*, vol. 51, no. 7, pp. 5772–5790, Jul. 2015. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1002/2015WR017169/full

[14] M. Schrön, M. Köhli, L. Scheiffele, J. Iwema, H. R. Bogena, L. Lv, E. Martini, G. Baroni, R. Rosolem, J. Weimar, J. Mai, M. Cuntz, C. Rebmann, S. E. Oswald, P. Dietrich, U. Schmidt, and S. Zacharias, "Improving calibration and validation of cosmic-ray neutron sensors in the light of spatial sensitivity," *Hydrol. Earth Syst. Sci.*, vol. 21, no. 10, pp. 5009–5030, Oct. 2017. [Online]. Available: https://www.hydrol-earth-syst-sci.net/21/5009/2017/

[15] M. Zreda, W. J. Shuttleworth, X. Zeng, C. Zweck, D. Desilets, T. Franz, and R. Rosolem, "COSMOS: The COsmic-ray soil moisture observing system," *Hydrol. Earth Syst. Sci.*, vol. 16, no. 11, pp. 4079–4099, Nov. 2012. [Online]. Available: https://www.hydrol-earth-syst-sci.net/16/4079/2012/

[16] A. Hawdon, D. McJannet, and J. Wallace, "Calibration and correction procedures for cosmic-ray neutron soil moisture probes located across Australia," *Water Resour. Res.*, vol. 50, no. 6, pp. 5029–5043, Jun. 2014. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1002/2013WR015138/abstract

[17] H. M. Cooper et al., "COSMOS-U.K.: National soil moisture and hydrometeorology data for environmental science research," *Earth Syst. Sci. Data*, vol. 13, no. 4, pp. 1737–1757, Apr. 2021, doi: 10.5194/essd-13-1737-2021.

[18] C. Brogi, H. R. Bogena, M. Köhli, J. A. Huisman, H.-J. Hendricks Franssen, and O. Dombrowski, "Feasibility of irrigation monitoring with cosmic-ray neutron sensors," *Geoscientific Instrum., Methods Data Syst.*, vol. 11, no. 2, pp. 451–469, Dec. 2022. [Online]. Available: https://gi.copernicus.org/articles/11/451/2022/

[19] C. Brogi, V. Pisinaras, M. Köhli, O. Dombrowski, H.-J. Hendricks Franssen, K. Babakos, A. Chatzi, A. Panagopoulos, and H. R. Bogena, "Monitoring irrigation in small orchards with cosmic-ray neutron sensors," *Sensors*, vol. 23, no. 5, p. 2378, Feb. 2023. [Online]. Available: https://www.mdpi.com/1424-8220/23/5/2378

[20] X. Han, H.-J. Hendricks Franssen, M. Á. Jiménez Bello, R. Rosolem, H. Bogena, F. M. Alzamora, A. Chanzy, and H. Vereecken, "Simultaneous soil moisture and properties estimation for a drip irrigated field by assimilating cosmic-ray neutron intensity," *J. Hydrol.*, vol. 539, pp. 611–624, Aug. 2016, doi: 10.1016/j.jhydrol.2016.05.050.

[21] D. Li, M. Schrön, M. Köhli, H. Bogena, J. Weimar, M. A. J. Bello, X. Han, M. A. M. Gimeno, S. Zacharias, H. Vereecken, and H.-J. H. Franssen, "Can drip irrigation be scheduled with Cosmic-ray neutron sensing?" *Vadose Zone J.*, vol. 18, no. 1, Jan. 2019, Art. no. 190053, doi: 10.2136/vzj2019.05.0053.

[22] C. Kamienski, J.-P. Soininen, M. Taumberger, R. Dantas, A. Toscano, T. S. Cinotti, R. F. Maia, and A. T. Neto, "Smart water management platform: IoT-based precision irrigation for agriculture," *Sensors*, vol. 19, no. 2, p. 276, Jan. 2019.

[23] D. Ottolini, I. Zyrianoff, and C. Kamienski, "Interoperability and scalability trade-offs in open IoT platforms," in *Proc. IEEE 19th Annu. Consum. Commun. Netw. Conf. (CCNC)*, Jan. 2022, pp. 1–6, doi: 10.1109/CCNC49033.2022.9700622.

[24] C. Kamienski, I. Zyrianoff, L. F. Bittencourt, and M. Di Felice, "IoTinuum: The IoT computing continuum," in *Proc. 20th Int. Conf. Distrib. Comput. Smart Syst. Internet Things (DCOSS-IoT)*, Apr. 2024, pp. 732–739.

[25] L. F. Bittencourt, R. Rodrigues-Filho, J. Spillner, F. De Turck, J. Santos, N. L. S. da Fonseca, O. Rana, M. Parashar, and I. Foster, "The computing continuum: Past, present, and future," *Comput. Sci. Rev.*, vol. 58, Nov. 2025, Art. no. 100782, doi: 10.1016/j.cosrev.2025.100782.

[26] H. Benyezza, M. Bouhedda, R. Kara, and S. Rebouh, "Smart platform based on IoT and WSN for monitoring and control of a greenhouse in the context of precision agriculture," *Internet Things*, vol. 23, Oct. 2023, Art. no. 100830, doi: 10.1016/j.iot.2023.100830.

[27] A. Comegna, S. B. M. Hassan, and A. Coppola, "Development and application of an IoT-based system for soil water status monitoring in a soil profile," *Sensors*, vol. 24, no. 9, p. 2725, Apr. 2024.

[28] A. Salam, *IoT in Cyber-Physical Systems*. Cham, Switzerland: Springer, 2024, pp. 349–364, doi: 10.1007/978-3-031-62162-8_13.

[29] M. Qian, C. Qian, G. Xu, P. Tian, and W. Yu, "Smart irrigation systems from cyber–physical perspective: State of art and future directions," *Future Internet*, vol. 16, no. 7, p. 234, Jun. 2024, doi: 10.3390/fi16070234.

[30] A. Morchid, R. Jebabra, H. M. Khalid, R. El Alami, H. Qjidaa, and M. Ouazzani Jamil, "IoT-based smart irrigation management system to enhance agricultural water security using embedded systems, telemetry data, and cloud computing," *Results Eng.*, vol. 23, Sep. 2024, Art. no. 102829, doi: 10.1016/j.rineng.2024.102829.

[31] P. Naga Srinivasu, M. F. Ijaz, and M. Woźniak, "XAI-driven model for crop recommender system for use in precision agriculture," *Comput. Intell.*, vol. 40, no. 1, p. 12629, Feb. 2024, doi: 10.1111/coin.12629.

[32] L. Gaspar, T. E. Franz, and A. Navas, "Integrating proximal gamma ray and cosmic ray neutron sensors to assess soil moisture dynamics in an agricultural field in Spain," *Agriculture*, vol. 15, no. 10, p. 1074, May 2025, doi: 10.3390/agriculture15101074.

[33] R. Díaz-Delgado, P. Buysse, T. Peres, T. Houet, Y. Hamon, M. Faucheux, and O. Fovert, "Mapping soil moisture using drones: Challenges and opportunities," in *Proc. 1st Int. Conf. Adv. Remote Sens. Shaping Sustain. Global Landscapes (ICARS)*, Aug. 2025, p. 18, doi: 10.3390/engproc2025094018.

[34] P. Harani, S. Gautam, S. K. Joshi, L. G. Asirvatham, and B. L. Rakshith, "Advancements in soil moisture estimation through integration of remote sensing and artificial intelligence techniques," *Sci. Total Environ.*, vol. 1001, Oct. 2025, Art. no. 180503, doi: 10.1016/j.scitotenv.2025.180503.

[35] M. Heistermann, T. Francke, L. Scheiffele, K. D. Petrova, C. Budach, M. Schrön, B. Trost, D. Rasche, A. Güntner, V. Döpper, M. Förster, M. Köhli, L. Angermann, N. Antonoglou, M. Zude-Sasse, and S. E. Oswald, "Three years of soil moisture observations by a dense cosmic-ray neutron sensing cluster at an agricultural research site in north-east Germany," *Earth Syst. Sci. Data*, vol. 15, no. 7, pp. 3243–3262, Jul. 2023, doi: 10.5194/essd-15-3243-2023.

[36] Z. Zhang, H. Ou, Y. Shi, Y. Ye, Y. Sang, S. Zhang, and J. Zhang, "Application of cosmic-ray neutron probes for measuring soil moisture in rocky areas of the taihang mountains, north China," *Vadose Zone J.*, vol. 22, no. 6, p. 20291, Nov. 2023, doi: 10.1002/vzj2.20291.

[37] X. Wang, R. Liu, M. Köhli, J. Marach, and Z. Wang, "Monitoring soil water content and measurement depth of cosmic-ray neutron sensing in the Tibetan Plateau," *J. Hydrometeorology*, vol. 26, no. 2, pp. 155–167, Feb. 2025, doi: 10.1175/jhm-d-23-0103.1.

[38] S. Emamalizadeh, A. Pirola, C. Alessandrini, A. Balenzano, and G. Baroni, "Comparison of soil water content from SCATSAR-SWI and cosmic ray neutron sensing at four agricultural sites in northern italy: Insights from spatial variability and representativeness," *Remote Sens.*, vol. 16, no. 18, p. 3384, Sep. 2024, doi: 10.3390/rs16183384.

[39] T. C. Morris, T. E. Franz, S. M. Becker, and A. E. Suyker, "Effect of biomass water dynamics in cosmic-ray neutron sensor observations: A long-term analysis of maize–soybean rotation in nebraska," *Sensors*, vol. 24, no. 13, p. 4094, Jun. 2024.

[40] Y. Zhang, S. Wu, W. Zhao, and J. Xiao, "Mesoscale soil moisture measurements along the rover route using the mobile cosmic-ray neutron sensing in the eastern Tibetan Plateau," *Geoderma*, vol. 450, Oct. 2024, Art. no. 117046, doi: 10.1016/j.geoderma.2024.117046.

[41] R. Mazzoleni, S. Emamalizadeh, G. Allegro, F. Vinzio, I. Filippetti, and G. Baroni, "Enhancing precision agriculture with cosmic-ray neutron sensing: Monitoring soil moisture dynamics and its impact on grapevine physiology," in *Proc. 16th Int. Conf. Precis. Agricult.*, 2024, pp. 1–13.

[42] S. K. Al-Mashharawi, S. C. Steele-Dunne, M. M. El Hajj, M. Schrön, C. Doussan, D. Courault, T. E. Franz, and M. F. McCabe, "Accounting for biomass water equivalent variations in soil moisture retrievals from cosmic ray neutron sensor," *Agricult. Water Manage.*, vol. 313, May 2025, Art. no. 109493.

[43] A. Cirillo, M. Caresana, L. F. F. Vero, A. Balenzano, D. Palmisano, G. Salatino, F. Ciavarella, C. Manganiello, and M. Rinaldi, "Multi-scale soil moisture measurements in a large bare field: Analysis of point and cosmic-ray neutron sensors as affected by tillage and rainfall," *SSRN*, Feb. 2024, doi: 10.2139/ssrn.4721161. [Online]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4721161

[44] G. Custódio and R. C. Prati, "Comparing modern and traditional modeling methods for predicting soil moisture in IoT-based irrigation systems," *Smart Agricult. Technol.*, vol. 7, Mar. 2024, Art. no. 100397.

[45] A. Torre-Neto, J. R. Cotrim, J. H. Kleinschmidt, C. Kamienski, and M. C. Visoli, "Enhancing soil measurements with a multi-depth sensor for IoT-based smart irrigation," in *Proc. IEEE Int. Workshop Metrology Agricult. Forestry (MetroAgriFor)*, Nov. 2020, pp. 78–82, doi: 10.1109/METROAGRIFOR50201.2020.9277562.

[46] J. Weimar, M. Köhli, C. Budach, and U. Schmidt, "Large-scale boron-lined neutron detection systems as a 3He alternative for cosmic ray neutron sensing," *Frontiers Water*, vol. 2, p. 16, Sep. 2020. [Online]. Available: https://www.frontiersin.org/article/10.3389/frwa.2020.00016

[47] H. Mavromichalaki et al., "Applications and usage of the real-time neutron monitor database," *Adv. Space Res.*, vol. 47, no. 12, pp. 2210–2222, Jun. 2011, doi: 10.1016/j.asr.2010.02.019.

[48] M. Köhli, J. Weimar, M. Schrön, R. Baatz, and U. Schmidt, "Soil moisture and air humidity dependence of the above-ground cosmic-ray neutron intensity," *Frontiers Water*, vol. 2, p. 15, Jan. 2021, doi: 10.3389/frwa.2020.544847.

[49] D. Power, M. A. Rico-Ramirez, S. Desilets, D. Desilets, and R. Rosolem, "Cosmic-ray neutron sensor Python tool (crspy 1.2.1): An open-source tool for the processing of cosmic-ray neutron and soil moisture data," *Geoscientific Model Develop.*, vol. 14, no. 12, pp. 7287–7307, Nov. 2021, doi: 10.5194/gmd-14-7287-2021.

[50] P. Ney, M. Köhli, H. Bogena, and K. Goergen, "CRNS-based monitoring technologies for a weather and climate-resilient agriculture: Realization by the ADAPTER project," in *Proc. IEEE Int. Workshop Metrology Agricult. Forestry (MetroAgriFor)*, Nov. 2021, pp. 203–208, doi: 10.1109/METROAGRIFOR52389.2021.9628766.

[51] M. Lathkar, *High-Performance Web Apps With FastAPI: The Asynchronous Web Framework Based on Modern Python*. New York, NY, USA: Apress, 2023, doi: 10.1007/978-1-4842-9178-8.

[52] F. Adelantado, X. Vilajosana, P. Tuset-Peiro, B. Martinez, J. Melia-Segui, and T. Watteyne, "Understanding the limits of LoRaWAN," *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 34–40, Sep. 2017.

[53] S. Lee, H. Kim, D.-k. Hong, and H. Ju, "Correlation analysis of MQTT loss and delay according to QoS level," in *Proc. Int. Conf. Inf. Netw. (ICOIN)*, Jan. 2013, pp. 714–717, doi: 10.1109/ICOIN.2013.6496715.

[54] E. O. Flückiger and R. Bütikofer, "Swiss neutron monitors and cosmic ray research at jungfraujoch," *Adv. Space Res.*, vol. 44, no. 10, pp. 1155–1159, Nov. 2009.

[55] S. Gianessi, M. Polo, L. Stevanato, M. Lunardon, T. Francke, S. E. Oswald, H. Said Ahmed, A. Toloza, G. Weltin, G. Dercon, E. Fulajtar, L. Heng, and G. Baroni, "Testing a novel sensor design to jointly measure cosmic-ray neutrons, muons and gamma rays for non-invasive soil moisture estimation," *Geoscientific Instrum., Methods Data Syst.*, vol. 13, no. 1, pp. 9–25, Jan. 2024. [Online]. Available: https://gi.copernicus.org/articles/13/9/2024/

[56] I. D. Zyrianoff, A. T. Neto, D. Silva, T. S. Cinotti, M. Di Felice, and C. Kamienski, "A soil moisture calibration service for IoT-based smart irrigation," in *Proc. IEEE Int. Workshop Metrology Agricult. Forestry (MetroAgriFor)*, Nov. 2021, pp. 315–319, doi: 10.1109/METROAGRIFOR52389.2021.9628393.

[57] H. R. Bogena, J. A. Huisman, R. Baatz, H.-J. H. Franssen, and H. Vereecken, "Accuracy of the cosmic-ray soil water content probe in humid forest ecosystems: The worst case scenario," *Water Resour. Res.*, vol. 49, no. 9, pp. 5778–5791, Sep. 2013. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1002/wrcr.20463/abstract

[58] C. A. van Diepen, J. Wolf, H. van Keulen, and C. Rappoldt, "WOFOST: A simulation model of crop production," *Soil Use Manage.*, vol. 5, no. 1, pp. 16–24, Mar. 1989, doi: 10.1111/j.1475-2743.1989.tb00755.x.

[59] A. de Wit, H. Boogaard, D. Fumagalli, S. Janssen, R. Knapen, D. van Kraalingen, I. Supit, R. van der Wijngaart, and K. van Diepen, "25 years of the WOFOST cropping systems model," *Agricult. Syst.*, vol. 168, pp. 154–167, Jan. 2019.

[60] R. C. Prati, F. Borelli, I. D. Zyrianoff, D. Silva, R. Togneri, and C. Kamienski, "IrrigaSim: An irrigation simulation, processing, and animation environment," in *Proc. IEEE Int. Workshop Metrology Agricult. Forestry (MetroAgriFor)*, Nov. 2021, pp. 305–309, doi: 10.1109/METROAGRIFOR52389.2021.9628455.

[61] A. De Wit. (Apr. 2024). *A Collection of Pcse Notebooks*. Accessed: Oct. 3, 2025. [Online]. Available: https://github.com/ajwdewit/pcse_notebooks

[62] S. Adla, F. Bruckmaier, L. F. Arias-Rodriguez, S. Tripathi, S. Pande, and M. Disse, "Impact of calibrating a low-cost capacitance-based soil moisture sensor on AquaCrop model performance," *J. Environ. Manage.*, vol. 353, Feb. 2024, Art. no. 120248, doi: 10.1016/j.jenvman.2024.120248.

[63] A. Fragkos, D. Loukatos, G. Kargas, E. Symeonaki, and K. G. Arvanitis, "Assessment of the TEROS 10 and TEROS 12 sensors in soil moisture measurement," in *Proc. E3S Web Conf.*, vol. 551, 2024, p. 03005.

[64] J. Iwema, M. Schrön, J. K. Da Silva, R. S. De Paiva Lopes, and R. Rosolem, "Accuracy and precision of the cosmic-ray neutron sensor for soil moisture estimation at humid environments," *Hydrological Processes*, vol. 35, no. 11, p. 14419, Nov. 2021, doi: 10.1002/hyp.14419.

[65] G. J. Sykora, S. E. Mann, G. Mauri, E. M. Schooneveld, and N. J. Rhodes, "Review of thermal neutron scintillators: Evaluation metrics and future prospects for demanding applications," *Opt. Mater., X*, vol. 24, Dec. 2024, Art. no. 100373, doi: 10.1016/j.omx.2024.100373.

[66] K. Zeitelhack, "Search for alternative techniques to helium-3 based detectors for neutron scattering applications," *Neutron News*, vol. 23, no. 4, pp. 10–13, Nov. 2012, doi: 10.1080/10448632.2012.725325.

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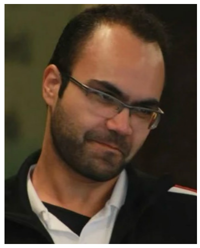

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