

AgroNIT: Innovating Precision Agriculture

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Abstract—Major global concerns considering food production include, not only meeting the increasing food demand but also meeting challenges that put significantly less strain on the environment, safeguard food quality and prevent wastage. To address the erstwhile challenges, the AgroNIT testbed has been designed to provide common access to facilities and services fostering the development and the validation through experimentation of novel cultivation practices, as well as to enable the digital transformation of Agriculture by applying advanced cultivation methods with digital tools and connected machinery. In this paper, we describe how AgroNIT brings emerging digital technologies to the disposal of farmers and scientists in order to advance agriculture practices in multi-fold dimensions: From improving production yield to minimizing the crops' environmental footprint and the effective management of fertilizers and pesticides to the optimization of the irrigation processes tailored to the needs of each crop cultivar. In AgroNIT smart decision support systems provide real-time AI-generated consultancy to farmers by relying on sensors that automate field measurements collection. Furthermore, agricultural scientists have access to a large repository of data measurements and novel data analytic services, being able to design, apply – along with the farmers – and validate new cultivation protocols. We provide examples demonstrating specific experiments and we show how the AgroNIT testbed benefits both farmers and agricultural scientists, thus enabling next-generation precision agriculture.

Index Terms—Precision Agriculture, IoT Testbed, Wireless Sensor Networks, Internet-of-Things, Connected Fields.

I. INTRODUCTION

A. Motivation

Today we are witnessing an unprecedented growth of novel technology-enabled solutions aiming to digitally transform the modern agriculture. Digital technologies such as *Internet-of-Things*, *Wireless Sensor Networks*, *Blockchain*, *Cloud & Edge Computing*, enabled through the latest communication technology standard 5G and B5G along with *Artificial Intelligence (AI)*-based services promise to change the traditional farming and cultivation and deliver substantial benefits not only to producers and consumers, but also to all actors participating in the entire food chain, thus improving the quality & safety of food products and reinforcing *sustainable* farming approaches.

Notwithstanding the proliferation of smart farming applications, the majority of current practices in applied research & experimentation in the field takes place manually with farmers and scientists collecting samples. Inevitably, this methodology suffers from many deficiencies including lack of accuracy, absence of real-time data, considerable delays,

erroneous manual work, and limited scalability, which lead to the creation of problematic artifacts and impede scientists to interpret results and draw valuable inference from the data.

Besides, major barriers currently exist on the path to accelerating the adoption of novel digital technologies in experimentation-based research in the agriculture domain. Namely: (i) *the complexity and fragmentation of the available digital solutions, which are vertically-integrated and tailored to specific field applications, require from researchers cumbersome efforts and programming skills to adapt and apply extensions on them, thus limiting their applicability*, (ii) *the lack or insufficiency of digital literacy, even among researchers*, and (iii) *the reliance on non-automated human-operated procedures and/or manual work*.

Experience from *Precision Agriculture* has shown that utilizing digital technology solutions towards a *holistic* management of crops, by relying on IoT-enabled sensing devices to collect field performance data, can mitigate the above deficiencies [1]–[3]. Therefore, enabling research in agriculture with advanced experimentation capabilities based on Precision Agriculture would not only provide a systematic and automated way of measurements collection, but also it would help researchers to improve the quality of their work, and attain important factors in their research methodology such as repeatability and reproducibility, to qualify their results.

Towards this direction, the AgroNIT testbed has been designed to enable advanced experimentation in the field of *Precision Agriculture* by consolidating heterogeneous digital technologies. Its aim is to create a foreground of innovation combining the disciplines of Agriculture and Information Technology, and to support researchers and experimenters conduct innovative experimentation-based research, providing them with state-of-the-art digital tools and services that can facilitate and increase the quality of the produced knowledge.

B. Methodology & Contribution

Facilitating advanced digital capabilities in an open-access agricultural testbed that interconnects fields, automates the procedures related to the collection of field data, combines measurements under a unified data model and applies on them AI data analytics to extract insights for optimizing yield & crops management, can significantly contribute to the faster

deployment of innovations in the field and to the creation of valuable knowledge.

The AgroNIT testbed, has emerged from the NITOS testbed¹ – a Future Internet experimentation facility [4] featuring heterogeneous digital technologies – addressing initially the need to provide a remotely accessible infrastructure for experimentation and validation in the emerging field of wireless sensor networks. It supports apart from IoT-enabled wireless sensing devices, *state-of-the-art* digital technologies such as Cloud & Edge Computing and Artificial Intelligence. Its aim is the implementation and validation of innovative *Precision Agriculture*-based solutions that will help farmers advance their crop management & production and scientists use a digital infrastructure that provides them with the appropriate instrumentation to design and conduct their experimentation with increased scientific rigor. The AgroNIT testbed is publicly available and remote accessible 24/7 through the Internet² and provides continuous performance monitoring of the fields, hosting several research experiments on differentiated crop management, especially in the areas of crop protection & phenology, smart irrigation, fertilization & harvesting.

This paper's contributions are summarized as follows:

- *A Novel Architecture consolidating Heterogeneous Digital Technologies:* AgroNIT is an experimentation-based platform that encompasses various heterogeneous digital technologies in the context of *Precision Agriculture* to deliver *Experimentation-as-a-Service* capabilities for advancing research in the agricultural research domain. Its architecture allows researchers to conduct experiments and test new mechanisms and protocols using remote sensing for field monitoring and collection of results, by relying on a modular wireless sensor network infrastructure, that can be extended and accommodate several wireless communication technologies. The physical deployment is composed of energy-autonomous wireless nodes located in more than 100 fields in Central and Northern Greece, spanning an area of 300 ha and it is already being used by more than 90 farmers (see Fig. 1). Researchers are offered the opportunity to use and combine those technologies and assess the performance efficiency of their solutions in terms of networking performance (delay, bit rate, error rate, etc.) and energy-cost measurements, and at the end select the most efficient ones that best meet their scenario requirements.
- *An AI-assisted Early Warning & Decision Support System for Optimized Field Management:* The EWS & DSS have been designed to combine artificial intelligence processes, cloud storage and cloud computing technologies, massive open data collection with customizable dashboards for automatically monitoring, classifying, managing, and predicting emerging field-performance changes. They incorporate statistical and math models that make use of AI algorithms to apply continuous risk management (e.g., forecast hazard weather conditions or crops diseases dispersion) and to

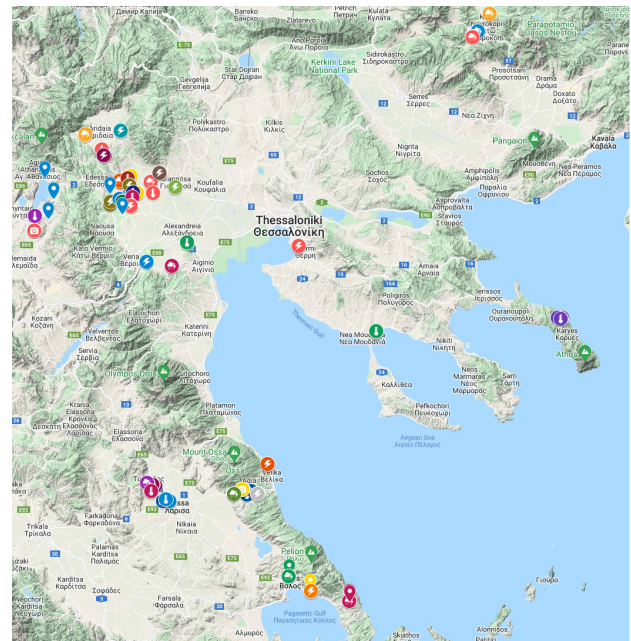


Fig. 1: Map of AgroNIT's Field Deployments, in Central & Northern Greece.

determine the optimal field management policy (e.g. farm planning, crop management & harvesting, soil and water conservation, pesticides, and disease control, fertilizing, etc.) and support real-time advisory and decision making.

- *Interactive Dashboards for Monitoring of Field Performance & Activity Management:* AgroNIT offers an interactive monitoring dashboard for displaying visual analytics, enabling advanced data discovery and offering real-time streaming capabilities to provide *online* diagnostic and predictive location-enabled analytics. Through interactive visual analytics, the historic records and the real-time data of different sources and fields can be combined and compared for the extraction of new knowledge.
- *A unique Data Management Model (DMM):* The adopted DMM fuses the different environmental & field measurements and integrates within it semantic data, metadata and analytics (e.g. summarization, aggregation, pattern discovery) to facilitate data storage & processing. The DMM is used to collate volumes of measurements into curated data-sets being easily exploitable by decision support systems for creating insightful recommendations to farmers and supporting linkage between the *in-situ* real-world settings data-sets and the querying attributes that a researcher requests.
- *Scalability, Reproducibility and Repeatability of Experimentation:* In AgroNIT experiments are designed to stimulate further new knowledge through exploitation and enrichment of the existing experimentation methodologies and datasets that can be open-accessed by the interested experimenters for reproducing, repeating and enhancing the findings. Moreover, given the large number of sensing devices deployed in the AgroNIT, scientists are able to conduct experimentation by allocating the minimum required number of resources to first validate their protocols and then gradually add more resources scaling out their solutions.

¹<http://nitos.inf.uth.gr/>

²<https://agronit.gr/#/el>

II. RELATED WORK

A. IoT Testbeds & Decision Support Systems in Agriculture

Leveraging IoT testbeds to apply *state-of-the-art* digital technologies for maximizing yield and improving quality while conserving natural resources have been in the epicenter of research [5], [6]. The development of testbed platforms for the implementation and test of new precision agriculture technologies that address the aforementioned challenges have significantly contributed in growing technology adoption rates. Through increased practical realism, agricultural testbeds offer the ability to researchers to design and test novel precision agricultural solutions with tools that allow verifiable and reproducible experimentation [7]. Emerging digital technologies (IoT, WSNs, AI/ML) enable the enrichment of precision agriculture with computer-assisted decision support systems (DSS) for optimized crop planning & farm management [8] contributing to real-time farming consultancy services. Over the last decades, research and development have led to a substantial number of AgriDSSs, the majority of which haven't been efficiently utilized in practice due to costly investments and technical complexities [9].

Optimized crop planning and resource management, based on WSNs and IoT, support optimized irrigation allow for finer precision degrees and adaptive cultivation protocols tailored to the individual crop needs while also considering local pedoclimatic conditions [10], [11]. The idea to combine sensors-based monitoring to feed simulations of cultivation algorithms, the results of which can orchestrate the operation of an adaptive controller for efficient irrigation planning has been tested by [11], [12]. Networks of weather stations, sensors assessing crops' water requirements and soil properties enabling continuous and real-time remote monitoring are leveraged to assess the water status and flow through the entire continuum of soil, plant, and atmosphere. Vera et al. [12] have proposed the concept of Precise Sustainable Irrigation (PSI). PSI is a real-time decision-making process that combines field variability with other plant-related parameters, and rainfall forecasts to increase water use efficiency and food production while lowering the energy and labor costs associated with irrigation. PSI requires intensive real-time in-field data acquisition obtained with Wireless Sensor Networks (WSN), and processing and analysis with the use of Information & Communication Technologies (ICT). A solution that poses the smart irrigation decision support system (SIDSS), proposed by Navarro-Hellin et al. [13], which aims to generate irrigation plans in a more efficient and accurate way with reasonable use of resources. SIDSS is composed of three components: a sensing device, a weather station, and a decision-making component. With the help of SIDSS, irrigation activities can achieve better performances with minimum water usages.

B. Computer Vision, Artificial Intelligence, Big Data Analytics & Machine Learning in Crop Protection

Crop protection is the science and practice of managing adverse factors related to the occurrence of diseases or infestations by pests and insects that can inhibit crop development

and cause a reduction in crop quality and hence crop value [14], [15]. To ensure crop's sustainability and performance, crop protection relies on the detection and accurate identification of imminent crop threats. However, the diagnosis of plant diseases requires visual examination and may present flaws due to its laborious and subjective nature [14].

To address this phenomenon, Computer Vision solutions combined with AI algorithms are utilized to automate the detection process of diseases in plants, by detecting patterns in images leading to the determination of the most discriminative characteristics for the efficient recognition of a disease or other infestation [16]. Classification models are used to categorize captured crop images into healthy or infected classes [16]. Regarding pest detection, insect traps can be used to improve the quality of image segmentation and accurately the process of insects' counting [14]. To monitor the population of aphids and identify the species present in a wheat fields, ML algorithms have been used for the image analysis based on training and classification methods [17]. Along with computer vision, Big Data and Machine Learning approaches have been also employed to model, detect and manage invasive species and weeds [15]. Some researchers have applied the Markov Random Fields (MRF) models in image, texture, and pattern analysis to model and predict the herbicide resistance [18]–[20] of *Avena sterilis* L. [21] or *Amaranthus tuberculatus* [22].

III. ARCHITECTURE

A. High-Level Architecture

The AgroNIT architecture consists of various innovative technological components that can be used for optimized & timely crop management through field performance monitoring, data analysis, and sharing of insights and results. Its aim is to empower the intelligence in smart farming and the experimentation-based research for farmers and agricultural scientists, respectively. Fig. 2 shows the schematic of the AgroNIT's three layer architecture. The core of the AgroNIT architecture lies in the data acquisition, management and application layers. More specifically:

The Data Acquisition Layer lies at the bottom, where the collection of field performance and sensing measurements take place. IoT-enabled devices equipped with lightweight and portable sensors (air & soil temperature and humidity, solar radiation, wind speed & direction, near-infrared (NIR) etc.) are employed for field and environmental measurement collection. Those sensors are attached to energy-autonomous wireless nodes, which form a wireless sensor network (WSN) and are able to communicate with each other by leveraging different communication technologies and protocols (e.g. ZigBee, LoRa WiFi, 4G-LTE/5G). The support of heterogeneous communication technologies allows for the formation of different and variable range wireless networks so that the sensing measurements can be transmitted reliably and with accuracy adapting to the transmission requirements and the spatial characteristics of the different terrains. Moreover, it allows the researchers to test and evaluate the use and the combinations of different technologies in terms of delay, latency, and throughput in

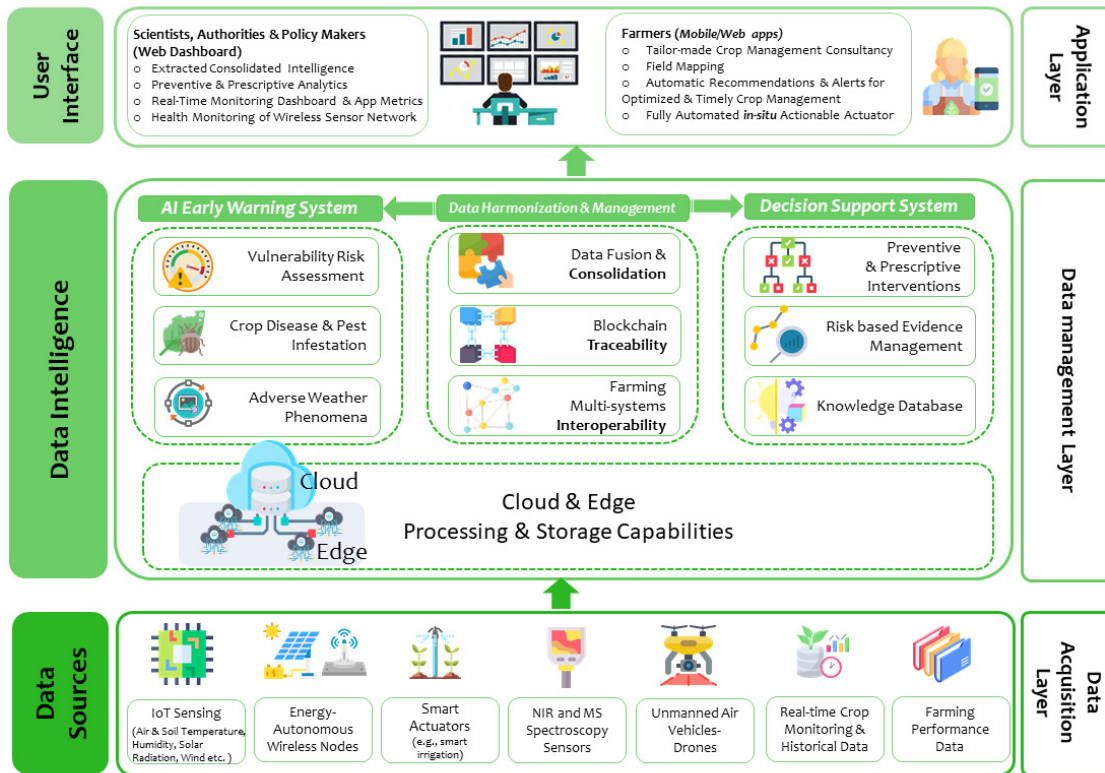


Fig. 2: The Three Layer Architecture of the AgroNIT platform.

the field application domain. The WSN facilitates the *in-situ* collection of field measurement data and allows for real-time monitoring of the field performance measurements. In sequence, the sensing data are being transmitted through the WSN to a cloud infrastructure for archiving & storage and for further processing & analysis.

In the *Data Management Layer* lies the intelligence of the AgroNIT platform. This is where the collected information is stored and processed, taking advantage of two options (i) either in a cloud-based data storage infrastructure capable of storing large data sets and AI/ML processing of computational-heavy tasks [23] or (ii) in the network edge for temporal storage and lightweight processing. It comprises three different components, namely (i) the Data Harmonization & Management, (ii) the AI-enabled Early Warning System, and (iii) the Decision Support System. The role of the Data Harmonization & Management component is to unify the different and heterogeneous data, stemming from the various sensing devices, under a common data model, by providing a shared data language for analytical applications to use. This simplifies the creation, aggregation, and analysis of the field measurement data and renders them directly exploitable by the various intelligence-enabled services. In addition, Blockchain technology is used to provide trusted exchange and sharing of data, through its decentralized nature, distributed storage, and robust and secure immutability features. Offering increased traceability makes Blockchain a trustworthy solution for backtracing critical information and historical data related to the stages and performance of crop cultivation, and to provide later on the interfaces for linking to the monitoring of the entire food value chain. Through the mechanisms (Data

Fusion & Consolidation, Blockchain Traceability, Farming Multi-systems interoperability) the data sources are offered in the Data Intelligence Layer to support the AI Early Warning System (AI-EWS) and the Decision Support System (DSS) for support decision-making with predictive and prescriptive actionable interventions, respectively. The AI-EWS provides data analytics for vulnerability risk assessment and proactive crop management. It uses AI to assess critical control measurements and proactively recommends to farmers actionable insights for timely crop management to mitigate adverse weather phenomena, crop diseases, and pest infestation. The DSS complements the EWS and provides data-driven decision support to help users apply optimized crop management, with regards to sustainable and environmental farming, meeting specific crop production goals (e.g., minimizing the environmental footprint, reducing wastage, optimizing the use of resources, maximizing inputs use efficiency and crop productivity, etc.).

At the top lies the *Application Layer*. Its aim is to simplify the visual presentation of the information and offer a deeper understanding of the crops' performance to the users. Following a user experience design (UXD) approach aims to improve the AgroNIT's usability and accessibility for the users. The users, which consist of two basic categories: (i) farmers & producers, and (ii) scientists, authorities and policy makers as well as engineers and platform operators, access the platform through web dashboards and mobile apps. According to their role, the API enables authorized control, facilitates access to data, enables data processing and sharing, and can be used to create dynamically informative graphs that can present the information annotated with valuable insights generated by the data intelligence layer. Farmers experience



Fig. 3: AgroNIT Wireless Nodes.

tailor-made individual crop management consultancy and analytical field mapping with performance metrics and intuitive color heatmaps. The visual presentation of the information is augmented with interactive recommendations and alerts for optimized and timely crop management. On the other hand, scientists can access consolidated knowledge, that combines in a systematic and automated way measurements and insights from different fields and crops, and are able to design and develop new algorithms and methodologies for optimized crop management based on AI predictive and prescriptive data analytics. Lastly, the platform operators are equipped with maintenance tools that monitor 24/7 the health and the operational functionality of the AgroNIT platform and are able to determine any possible faulty operation and take the appropriate countermeasures.

B. The Nodes of the AgroNIT Wireless Sensor Network

The WSN consists of solar-powered, energy autonomous devices (wireless nodes) see Fig. 3. Each node is equipped with various field-based electronic sensing modules (e.g., capacitive soil temperature, water potential sensor, air temperature & humidity sensor, precipitation sensor etc.), micro-controllers and wireless transceiver modules to allow for the monitoring, recording, and transmission of the sensing data to the cloud infrastructure. Particularly, the devices composing the AgroNIT WSN feature 5 discrete categories.

- The *Agro Node* is a field wireless node equipped with low-cost sensors for crop, soil and environmental monitoring of the most important parameters (e.g., air temperature & humidity, soil temperature & water potential, and leaf wetness) affecting crop development. It is installed at crop level in order to collect measurements that are representative of the pedoclimatic conditions affecting the crop development.
- The *Weather Station Node* is also equipped with low-cost sensors to measure with increased accuracy key climatic parameters affecting crop development, such as wind speed & direction, precipitation, and solar irradiance. It is normally located at the edge of the field complementing the *Agro node* to minimize potential distortion of measurements due to the existence of natural obstacles, like the crop canopy.
- The *EyeFruit Node* is installed at tree level to monitor fruits' growth rate and evaluate their maturity status. Leveraging a low-cost solution that is based on the Raspberry Pi Camera

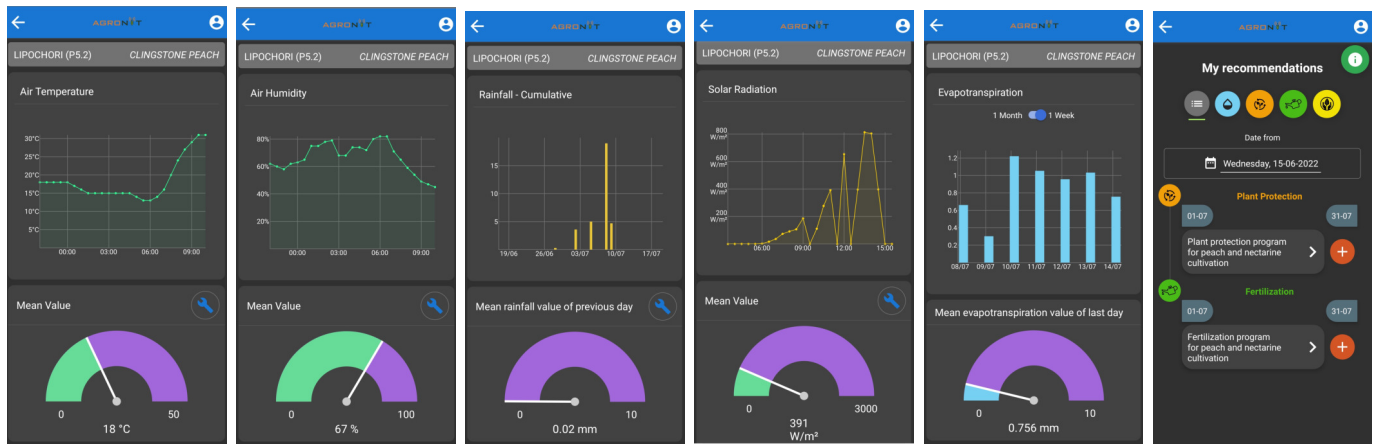
Module V2³, the node captures regularly field-based images of the targeted fruit(s). A Faster R-CNN Deep Learning model [24] is trained using a custom dataset to detect fruits and then the F, B, Alpha Matting segmentation network [25] is applied to predict the foreground and background on the captured images.

- The *SmartTrap Node* is an insect trapping device that hosts a fully autonomous monitoring system on its ceiling. The monitoring system features the same camera sensor as the *EyeFruit Node* that captures images of a sticky card that is placed at the bottom of the trap. The acquired data are continuously streamlined to the AgroNIT Cloud for storage and further analysis using 5G communication interfaces.
- The *Gateway Node* provides access to the backbone network and connects the WSN with the end users through the Internet. Its main role is to transmit the field measurements collected by the nodes of the WSN to the cloud infrastructure with increased reliability by using multiple wireless interfaces and different communication technologies. The collected measurements are aggregated and then are transmitted to the AgroNIT's proprietary cloud platform. Transmissions are scheduled to occur at regular time intervals during the day through 4G/5G wireless connection links or through Ethernet in the case where cable network is available. A complementary role of the Gateway node is to support health monitoring and the remote and on-the-fly configuration of each sensing device using an asynchronous wireless communication protocol for the transmission and execution of administrator commands and code updates.

C. AI Early Warning System & Decision Support System

Supporting data-driven decision-making and early warning notifications with tools for generating advisory tailored to the specific needs of each type of cultivation aims to integrate intelligence into cultivation practices such as irrigation, fertilization, crop protection, harvesting, pruning etc. To enable this, the AgroNIT cloud infrastructure offers high-performance computing and storage capabilities along with AI data analytics services. Flows of raw data measurements are continuously streamlined to the AgroNIT cloud from the deployed WSN in the fields. To facilitate the processing of the data measurements, a common data model is utilized to orga-

³<https://www.raspberrypi.com/products/camera-module-v2/>



(a) Sensing Data - Air-Temperature. (b) Sensing Data - Air-Humidity. (c) Meteorological Data - Rainfall. (d) Meteorological Data - Solar Radiation. (e) Predictive Analytics - Evapotranspiration. (f) Prescriptive Analytics for Decision Support.

Fig. 4: AgroNIT Mobile Application - User's Dashboard.

nize the different measurements and to capture their spatio-temporal (time and location) characteristics. The records of the measurements fitted into the data model are fed to the real-time time series data agricultural algorithms to provide a) an estimation of real crop needs in water and nutrients, based on the occurring weather & growing conditions; b) an assessment of the current crop's phenological status by monitoring parameters such as the accumulated chilling and growing degree hours; as well as c) a forecast of potential threats from biotic and abiotic factors, such as diseases, pests or adverse weather phenomena, by analysing local climatic conditions and weather forecasting, respectively. Based on the algorithms outputs the Early Warning System and the Decision Support System are able to automatically generate warnings and/or recommendations for the end-users or for a field-based actuation system in the form of commands.

IV. USE CASES

To demonstrate the AgroNIT testbed, two use cases are described. The first shows how a peach grower benefits from the AgroNIT services. The second one shows how an agricultural scientist uses the available tools and services to design eco-friendly irrigation management protocols for pear trees.

End-user - Farmer: In this case scenario, a peach producer uses the AgroNIT's platform to receive (a) regular updates on the weather forecast and microclimatic field conditions reports, as well as (b) recommendations on the suitability of conducting a field task (i.e., irrigation, fertilization, and spraying). These recommendations are automatically generated by leveraging the available 48h weather forecast report, and by considering the agricultural equipment the grower uses as well (i.e., irrigation or spray nozzles' type). The farmer continuously monitors the weather and local (pedo)climatic conditions in the field and (s)he leverages the offered AI services to forecast potential adverse factors, such as an insect or disease infestation that may affect crop performance. All this information is being consolidated under a Decision Support and Early Warning System that have been designed to facilitate the daily task scheduling performed by the farmer as well as to recommend preventive measures for plant protection. Fig. 4 shows the information presented to the farmers' mobile phone.

End-user - Agricultural research scientist: This scenario focuses on the evaluation of water use efficiency (water volume m^3 per produced kg) and cost-effectiveness (€ per produced kg) of irrigation practices applied in the cultivation of pear tree crop (*Pyrus Communis* L., cv. Krystali) grown in the region of Tynavos, Larissa for the summer of 2021. Leveraging the customizable smart irrigation model (SIM) integrated into the AgroNIT platform, a researcher is able to devise irrigation management protocols during a growing season, based on (a) the local climate conditions, as measured by the WSN; (b) on the field, crop & irrigation system attributes; as well as (c) on the Key Performance Indicators (KPIs) defined at the start of the season. To achieve this, the user is able to modify a set of parameters that are specific to the crop (i.e. crop coefficient, K_c [26]), to the irrigation supply (i.e. irrigation coefficient, I_c), as well as to the irrigation cost (€/m³) that are considered by the SIM to compute the irrigation volume to be supplied. Table I lists the model parameters and relevant KPIs set for the current use case. The SIM features the Penman-Monteith equation [26] that -in this case- has been parameterized to compute the daily pear tree evapotranspiration, the required irrigation volume (m^3), duration (min), and interval (days), as well as the recommended irrigation doses (min) according to the estimated interval, on a daily basis. Based on this information, an agricultural scientist is able to define the optimal irrigation scheme to meet the crop water needs. In Table II the weekly sums of the aforementioned parameters are computed for the period July-August 2021 for cv. *Krystali* grown in Tynavos, Greece. Since the irrigation interval is estimated to be three days for the specific pilot field, the total irrigation volume should be applied in two doses per week. Hence, the duration per dose is half of the total duration. In this case scenario the user also decided to apply post-harvest deficit irrigation (50% of ET_c) to assess its impact on the potential water savings and water-use efficiency vs. the conventional method. This means that the supplied water (I_{dt}) is the half of the real crop water needs to induce mild water stress. Moreover, by setting an average cost (€) per m^3 of irrigated water volume the calculation of the potential cost-effectiveness of the alternative irrigation treatment is enabled. Table III presents a comparative analysis between the conventional and the smart irrigation treatment, showing the impact of the latter

TABLE I: LIST OF PARAMETERS INCORPORATED INTO THE AGRONIT SMART IRRIGATION MODEL FOR PEAR CV. KRYSTALI.

Source	Category	Parameter Description
WSN	Climate & Pedoclimate	Air temp. (°C), Sun irradiation (W/m^2), Wind speed (m/s), Precipitation (mm), Soil Water Potential ($cbar_s$)
Field Observations	Soil mechanical properties	Composition, Infiltration rate
	Irrigation system properties	Nozzle Type, Water Supply Rate
	Crop attributes	Age, Phenophases, Expected Productivity, Training system, Planting density
User Defined	Crop Coefficient	$K_c = [0.3 - 0.9]$ [26]
	Irrigation Coefficient	$I_c = 100\%$ (full irrigation), $I_c = 50\%$ (deficit irrigation)
	Irrigation Cost	0.3 ($€/m^3$)
	Total Yield	2250 kg
	KPIs	Water Savings (%), Use Efficiency (m^3/kg), Cost Effectiveness ($€/kg$)

TABLE II: WEEKLY SUMS OF CROP EVAPOTRANSPIRATION (ETC), TOTAL IRRIGATION REQUIREMENTS (IDT) & DURATION (IT) FOR CV 'KRYSTALI' FOR DIFFERENT IRRIGATION COEFF (IC) FROM JULY TO AUGUST 2021.

Date	Ic (%)	ETc (mm)	Idt (mm)	It (min)	It/dose (min)
27.07.21	100	24.5	28.8	495	247
03.08.21	100	25.2	29.6	508	254
10.08.21	100	21.8	25.6	439	220
17.08.21	50	19.5	11.4	196.5	98.5
24.08.21	50	18.4	10.8	185.5	92.5
31.08.21	50	21.9	12.8	111	55.5

TABLE III: COMPARATIVE ANALYSIS OF THE CONVENTIONAL VS. THE SMART IRRIGATION TREATMENT ON WATER IRRIGATION, NEEDS, SAVINGS, USE-EFFICIENCY & IRRIGATION COST DURING 2021.

Treatment	Irrigated (m^3)	Savings (%)	Efficiency (m^3/kg)	Cost (€)
Conventional	500.7	—	0.22	150.2
Smart	402.9	19.5	0.18	120.9

on water-use efficiency, total water savings, and irrigation cost.

V. CONCLUSIONS

AgroNIT is an open-access agricultural testbed, designed with an aim to facilitate experimentation in the context of precision agriculture and accelerate the digital transformation of the field with smart farming applications. In AgroNIT, a highly modular architecture has been adopted to increase the degree of flexibility in utilizing the provided heterogeneous technologies and hence offer the end-users the means (digital technologies, equipment and services) to design, create and validate innovative cultivation protocols focusing on a wide spectrum of areas of the primary and secondary production sectors. AgroNIT supports data-driven decision-making in a direct, comprehensible and customized way providing guidance on timely planning and optimized crop management.

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REFERENCES

- [1] Z. Zhai, J. F. Martínez, V. Beltran, and N. L. Martínez. Decision support systems for agriculture 4.0: Survey and challenges. *Computers and Electronics in Agriculture*, Elsevier, 170:105256, 2020.
- [2] Vincent Bonneau, Bertrand Copigneaux, L. Probst, and B Pedersen. Industry 4.0 in agriculture: Focus on iot aspects. *Directorate-General Internal Market, Industry, Entrepreneurship and SMEs*, 2017.
- [3] Matthieu De Clercq, Anshu Vats, and Alvaro Biel. Agriculture 4.0: The future of farming technology. *Proceedings of the World Government Summit, Dubai, UAE*, pages 11–13, 2018.
- [4] Dimitris Giatsios, Apostolos Apostolaras, Thanasis Korakis, and Leandros Tassioulas. *Methodology and Tools for Measurements on Wireless Testbeds: The NITOS Approach*, pages 61–80. Springer Lecture Notes in Computer Science (LNCS), vol. 7586 2013, 01 2013.
- [5] Suat Irmak and William R Rathje. Plant growth and yield as affected by wet soil conditions due to flooding or over-irrigation. *NebGuide*, 2004.
- [6] Suat Irmak, Michael J Burgert, HS Yang, Kenneth G Cassman, Daniel T Walters, William R Rathje, Jose O Payero, Patricio Grassini, Mark S Kuzila, and Kelly J Brunkhorst. Large-scale on-farm implementation of soil moisture-based irrigation management strategies for increasing maize water productivity. *Transactions of the ASABE*, 2012.
- [7] Abdul Salam and Syed Shah. Internet of things in smart agriculture: Enabling technologies. In *2019 IEEE 5th World Forum on Internet of Things (WF-IoT)*, pages 692–695. IEEE, 2019.
- [8] Matjaž Kukar, Petar Vračar, Domen Košir, Darko Pevec, and Zoran Bosnić. Agrodss: A decision support system for agriculture and farming. *Computers and Electronics in Agriculture*, 161:260–271, 2019.
- [9] Jessica Lindblom, Christina Lundström, Magnus Ljung, and Anders Jonsson. Promoting sustainable intensification in precision agriculture: review of decision support systems development and strategies. *Precision Agriculture*, 18(3):309–331, 2017.
- [10] T. Ojha, S. Misra, and N. S. Raghuvanshi. Internet of things for agricultural applications: The state of the art. *IEEE Internet of Things Journal*, 8(14):10973–10997, 2021.
- [11] YA Al-Mulla, S Siddiqi, I McCann, M Belhaj, and H Al-Busaidi. Integrating new technologies into the effective planning of irrigation schedules towards efficient water use and minimum loss. In *VIII International Symposium on Irrigation of Horticultural Crops 1150*, pages 67–74, 2015.
- [12] J Vera, I Abrisqueta, W Conejero, and MC Ruiz-Sánchez. Precise sustainable irrigation: A review of soil-plant-atmosphere monitoring. In *VIII International Symposium on Irrigation of Horticultural Crops 1150*, pages 195–202, 2015.
- [13] Honorio Navarro-Hellín, Jesus Martinez-del Rincon, Rafael Domingo-Miguel, Fulgencio Soto-Valles, and Roque Torres-Sánchez. A decision support system for managing irrigation in agriculture. *Computers and Electronics in Agriculture*, 124:121–131, 2016.
- [14] Diego Inácio Patrício and Rafael Rieder. Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. *Computers and electronics in agriculture*, 153:69–81, 2018.
- [15] Ryan HL Ip, Li-Minn Ang, Kah Phooi Seng, JC Broster, and JE Pratley. Big data and machine learning for crop protection. *Computers and Electronics in Agriculture*, 151:376–383, 2018.
- [16] Jayme Garcia Arnal Barbedo. A review on the main challenges in automatic plant disease identification based on visible range images. *Biosystems Engineering*, 144:52–60, 2016.
- [17] Tao Liu, Wen Chen, Wei Wu, Chengming Sun, Wenshan Guo, and Xinkai Zhu. Detection of aphids in wheat fields using a computer vision technique. *Biosystems Engineering*, 141:82–93, 2016.
- [18] Jan-Olof Johansson. Parameter-estimation in the auto-binomial model using the coding- and pseudo-likelihood method approached with simulated annealing and numerical optimization. *Pattern Recognition Letters*, 22(11):1233–1246, 2001.
- [19] S. Geman and C. Graffigne. Markov random field image models and their applications to computer vision. *Markov Random Field Image Models and Their Applications to Computer Vision*, pages 1496–1517, 1987. Cited By :1 Export Date: 4 February 2022.
- [20] S Geman and D Geman. Stochastic relaxation, gibbs distributions and the bayesian restoration of images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 6(6):721, 1984.
- [21] Beatriz Diaz, Angela Ribeiro, Ricardo Bueno, Domingo Guinea, Judit Barroso, David Ruiz, and Cesar Fernandez-Quintanilla. Modelling wild-oat density in terms of soil factors: A machine learning approach. *Precision Agriculture*, 6(2):213–228, 2005.
- [22] Jeffrey A Evans, Patrick J Tranel, Aaron G Hager, Brian Schutte, Chenxi Wu, Laura A Chatham, and Adam S Davis. Managing the evolution of herbicide resistance. *Pest Management Science*, 72(1):74–80, 2016.
- [23] Influx db, a time series platform. <https://www.influxdata.com/products/influxdb-overview/>, August 2022.
- [24] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *Adv. in neural inf. process. syst.*, 28, 2015.
- [25] Marco Forte and François Pitié. *f, b, alpha* matting. *arXiv preprint arXiv:2003.07711*, 2020.
- [26] Richard G Allen, Luis S Pereira, Dirk Raes, and Martin Smith. Fao irrigation and drainage paper no. 56. *Food and Agric. Org. of the U.N.*, 56(97):e156, 1998.