Scalable Architecture and Intelligent Edge with 5G-Advanced, MEC, IoT, UAVs and AI for a Sustainable Agriculture and Food Operations

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ABSTRACT Efficient agricultural production increasingly relies on advanced technologies to address the challenges of sustainability, scalability, and cost-effectiveness. This paper investigates the application of 5G-Advanced networks as a transformative enabler for modern agriculture, offering significant efficiency and cost advantages over traditional wireless sensor networks. By leveraging cutting-edge technologies such as IoT, Multi-access Edge Computing, and Artificial Intelligence/Machine Learning/Deep Learning, this applied research study introduces an innovative framework that shifts actuation decisions from user equipment to the edge, enhancing scalability and simplifying device design. The proposed framework integrates drone-supported intelligent robotics with IoT-driven edge computing, tailored to the unique demands of rural agricultural areas. Case studies from an award-winning TM-Forum catalyst project validate the framework's efficacy in architecture modeling, focusing on drone-assisted 5G networks, advanced orchestration, network slicing, and ultralow-latency communication. These case studies emphasize precision and scalability in critical agricultural operations such as weeding, irrigation, harvesting, crop, animal and storage monitoring. The findings underscore the potential of 5G-Advanced networks to revolutionize agriculture by enabling precise, efficient, and sustainable practices. This approach addresses diverse system requirements and offers a robust solution for future-ready agricultural technologies, paving the way for a scalable and resilient agricultural ecosystem.

KEYWORDS 5G-Advanced network connectivity, drones/UAVs, edge computing, intelligent robotics, IoT sensors, network slicing, real-time inference, ultralow latency.

1. INTRODUCTION

To address crop or livestock challenges effectively rather than merely detecting issues, it is essential to integrate artificial intelligence (AI) algorithms and robotics to enable real-time system operations. The implementation of 5G technology is pivotal in facilitating the high-speed connectivity and low-latency communication necessary for such advanced, responsive agricultural systems.

Achieving productivity and sustainability in agriculture is often hindered by the prohibitive costs of advanced technologies for smaller farms. Modern agriculture is characterized by multifaceted challenges that impact both farmers and technology providers. From the perspective of farmers, critical issues include labor shortages, lack of technical skills, soil degradation, water limitations, crop and livestock losses, and the increasing demand for resilient plant and animal species. Simultaneously, communication service providers (CSP's), including telecommunications and technology companies, face significant obstacles such as limited rural mobile network coverage, the digital divide, challenging agricultural environments, and fragmented data infrastructures. These barriers collectively impede the deployment of transformative solutions for the agricultural sector.

The emergence of 5G technology represents a transformative step in the digitization of agriculture, enabling tailored solutions that address the unique operational goals of farmers. This transition is further amplified by the “5G-Advanced” technology, the newest release of 5G (some other papers call it “Beyond 5G”), which integrates AI-driven functionalities into 5G radio access networks, core networks, and operational frameworks. Building upon our prior research [1], which explored the convergence of 5G private networks, edge computing, machine learning (ML), and robotic automation to tackle agricultural challenges, this paper extends these findings. It reviews the literature, explores the advanced capabilities of 5G-A, adds new use cases and deals with a comprehensive analysis of service orchestration, intent-driven order management and network slicing (NS), adding new results and a discussion on adaptability on scalability issues.

In particular, this work focuses on high-demand agricultural applications that necessitate extreme technical specifications, such as high bandwidth demand in uplink, ultra-low latency for fast inferencing and dense sensor networks. Furthermore, a detailed description is presented for the deployment of a chain of drones to extend 5G coverage across agricultural areas with no public availability, illustrating the potential of this framework to address technical and operational challenges in rural settings.

The remainder of this paper is structured as follows: Section 2 provides a concise review of the relevant literature. Section 3 outlines our proposed solution blueprint, while Section 4 discusses selected use cases spanning crop, food, and animal life cycles. Section 5 examines the solution implementation from the perspectives of both farmers and service providers in a structured five-step approach. Subsequently, Section 6 presents the results and discussion, and Section 7 concludes the paper by summarizing the key findings and insights.

2. SHORT REVIEW OF THE CURRENT LITERATURE

Challenges in agriculture are exacerbated by the remote nature of farming locations, limited access to technology, labor shortages, and societal perceptions of farming, as noted in [2]. The authors provide an overview of smart farming, including use cases involving autonomous robots and sensors, but relying exclusively on a poor internet connectivity. They identify the rapid growth of these technologies as a challenge due to the potential for increased e-waste from frequent hardware upgrades. Complexities of optimizing large-scale decision-making remain unresolved.

Research in [3] highlights an IoT-based architecture framework (from 2019) tailored for the agri-food sector, encompassing a coherent set of architectural viewpoints and comprehensive guidelines. This framework was applied to 19 diverse use cases spanning arable farming, dairy production, fruit and vegetable cultivation, and meat supply chains. Its implementation enabled consistent, timely, and structured modeling of these use cases, aligning with the large-scale industrial objectives of the European IoF2020 project. However, the study's primary weakness lies in its lack of concrete reference architectures and insufficient attention to real-time communication functionalities, such as immediate machine control via advanced network interfaces.

The article in [4] presents a detailed survey of state-of-the-art IoT advancements in agriculture from 2019. It explores agricultural network architectures, platforms, and topologies that provide access to IoT backbones, aiding farmers in increasing crop yields. The study also offers an extensive review of emerging IoT applications, devices, sensors, communication protocols, and cutting-edge innovations tailored for agriculture. Instead, the paper in [5] from 2022 investigates the tools and equipment used in applications of wireless sensors in IoT agriculture, and the anticipated challenges faced when merging technology with conventional farming activities. The primary contribution of the work in [6] (from 2023) is the development of an AI and IoT framework tailored for smart and sustainable agriculture. This framework addresses challenges arising from the fragmented nature of farming production systems, and aims to advance solutions that resolve inefficiencies and improve coherence across agricultural processes, thereby supporting sustainable and innovative farming practices.

The following four articles each explore distinct aspects of smart agriculture, emphasizing the transformative role of AI and IoT technologies in improving efficiency and sustainability in farming practices. Article [7] provides a systematic review of ML applications in agriculture, highlighting their use in soil parameter prediction, disease detection, crop quality assessment, and livestock monitoring. The review paper [8] focuses on artificial intelligence in agriculture, surveying AI/ML methods such as expert systems, image processing, and robotics, while discussing their role in enhancing productivity and sustainability. Article [9] emphasizes the potential of deep learning (DL) in agriculture, reviewing 120 studies that cover applications like disease detection, plant classification, and smart irrigation. Article [10] specifically addresses deep-learning-based object counting in agriculture, analyzing recent advancements, datasets, and methodologies.

Five years ago, the studies in [11] and [12] emphasized the integration of IoT and wireless sensor networks as essential for smart agriculture, utilizing technologies such as ZigBee, WiFi, SigFox, and LoRaWAN for non-real-time data collection in applications like irrigation, soil monitoring, pest control.

Table 1
Different wireless communication technologies and their characteristics

Parameters	ZigBee	WiFi	NB-IoT	LoRa (PHY+WAN)	SigFox
Standard	IEEE 802.15.4	IEEE 802.11a/b/g/n	3GPP rel. 13	ITU-T Y.4480	IEEE 802.15.4g
Frequency band	868/915 MHz and 2.4 GHz (free)	2.4 GHz (free)	868-915 MHz (licenced)	868/923 MHz (free)	868/915 MHz (free)
Data rate	20, 40 and 250 kbps	11-54 and 150 Mbps	160-200 kbps (UL), 160-250 kbps (DL)	250 bps - 22 kbps	100 bps
Latency	30 ms	50 ms	1s	~1-3 s	~2-8 s
Max range (distance)	100 m	100 m	1-25 km	15 km	10 km
Network size	65,000 nodes	32 nodes	1,000 nodes	10,000 nodes /BS	1,000,000 nodes /BS
Network topology	point-to-point, tree, star, mesh	point-to-hub	cellular system	star-of-stars	star
Limitations	LoS between sensors and agent	power consumption, long access time	does not support the handover	low data rate	very low data rates

The review in [13] adds Narrowband IoT (NB-IoT) to the above list, and validates communication times (see Table 1). Field tests and analysis reveal that ZigBee is most effective for monitoring in facility agriculture, whereas LoRa and NB-IoT are better suited for field agriculture scenarios. A recent study from 2023 presented in [14] investigates the primary applications of IoT and unmanned aerial vehicles (UAVs) in smart farming, with an emphasis on network functionalities and connectivity requirements. It provides a distance-based classification of communication technologies employed in IoT systems. To address connectivity limitations, the paper evaluates meshed LoRa WAN gateways as a solution to connectivity challenges.

Instead, the authors in [15] emphasize the pivotal role of cellular technologies in enabling connectivity for IoT-based sensors and smart farming machinery across expansive agricultural fields, where short-range communication proves inadequate. Future agricultural machinery, such as UAVs, is expected to leverage cellular networks for real-time communication during operations over large areas. The focus is increasingly shifting toward advanced technologies such as standalone 5G and 5G-Advanced, which are poised to replace legacy wireless sensor networks, ensuring continuous connectivity for smart farming systems. Similarly, the studies presented in [16] and [17] review the advancements of 5G IoT and Big Data in smart agriculture, providing insights into its development, architecture, enabling technologies, and application scenarios. They also discuss practical implementations, highlight the transformative impact of 5G on agricultural practices, and addresses associated key technologies, challenges, and scientific problems.

Nevertheless, the aforementioned studies lack comprehensive, actionable frameworks for effectively integrating these technologies into scalable and practical agricultural solutions.

The current landscape reveals additional barriers, such as:

• data collection practices: inconsistent integration of IoT sensors limit the accuracy and usability of agricultural data;

• limited robotic adoption: agricultural robotics show promise but remain in early stages, with high costs limiting use, especially for smaller farms;

• connectivity challenges: limited rural 5G availability prevents the implementation of advanced solutions that rely on high-speed, low-latency networks;

• environmental impacts: harsh conditions like extreme weather, dust and debris reduce IoT and autonomous system reliability;

• insufficient data processing: a lack of edge computing infrastructure in rural areas delays real-time processing and actionable insights.

Related to this last point, the article [18] explores the integration of Multi-Access Edge Computing (MEC) into mobile network architectures, highlights MEC enablers and network slicing, reviews optimization approaches for MEC resources and QoS parameters, and proposes an architectural framework. The paper [19] reviews the integration of MEC and NS for efficient resource allocation, examines their role in 5G-Advanced systems and identifies current challenges. Edge computing, when integrated with 5G, satellite imaging [20], AI and IoT, offer transformative potential for agriculture. However, these advancements require robust rural connectivity, ruggedized equipment, and scalable architectures to overcome existing barriers.

Finally, the article in [21] introduces the scope of Agriculture 5.0, detailing the key features and technologies anticipated in 6G-IoT communication systems. It emphasizes the critical role of these emerging technologies in advancing smart agriculture and concludes with an exploration of future challenges and opportunities in the field.

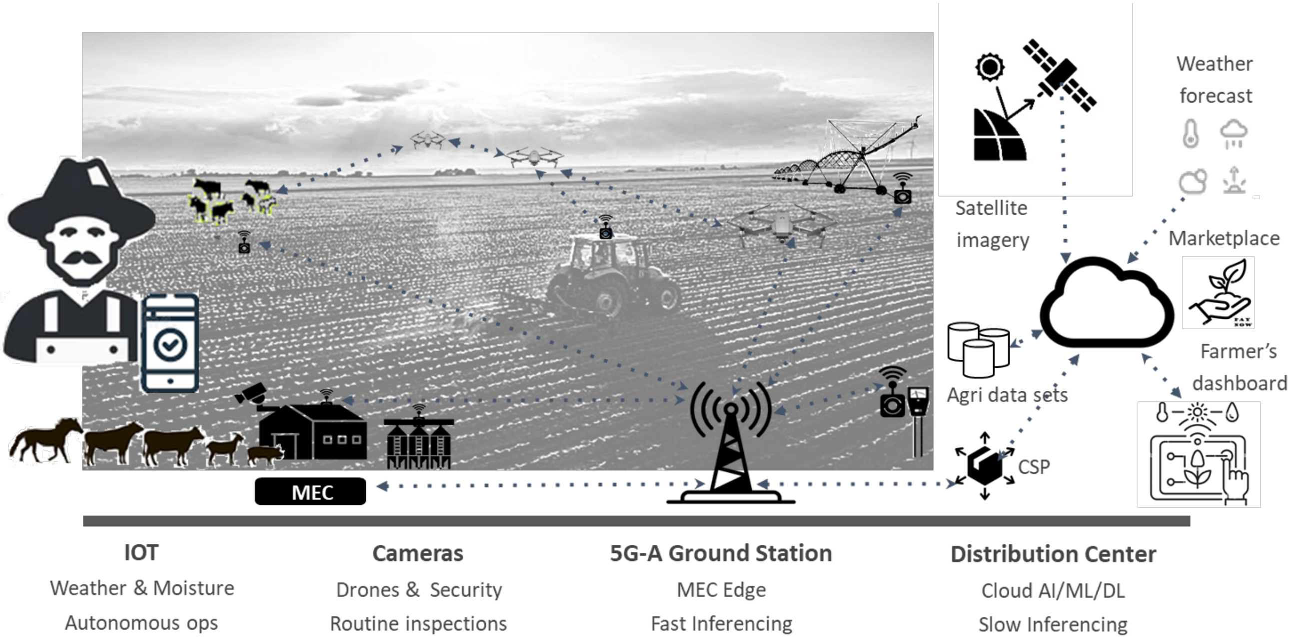


Figure 1. High level solution: 5G-drone/MEC deployment for smart agriculture (potential CSP offering to farmers)

3. A SCALABLE ARCHITECTURE

Our goal is to create a unified reference architecture tailored for smart agricultural use cases, leveraging 5G-Advanced, private networks, drones, cameras, agricultural robots, sensor networks, edge computing, cloud computing, AI/ML/DL, computer vision, satellite imagery, weather forecast, historical data sets and marketplaces.

This framework addresses key challenges such as enabling farmers to access AI-driven technology remotely, scaling AI solutions for larger farms, and providing outcome-based recommendations by integrating historical and real-time data. Real-time insights will improve in-season decision-making for crop productivity and animal health, while drones and robotic systems, enhanced by AI, optimize operational efficiency (see Fig.1).

A scalable architecture enables the farmer to leverage cutting-edge AI and 5G-Advanced technologies to have intent-based farming management tools. Emerging technologies such as generative AI can be also used to enhance context and usability to capture intent and provide real-time feedback for the farmer.

Farmers can utilize an enterprise portal to access, purchase, and manage various agricultural use case services. Through the chatbot or direct communication, farmers can express their needs, leading to the preparation and loading of customized offers in the operator portal. The farmer can then conveniently order and manage their assets via this portal. Upon logging in, the dashboard serves as the starting point, displaying tailored offers prioritized through a smart offering mechanism. An automated infrastructure offers real-time data, featuring fertility maps, weed/crop data sets, sensor feeds, and productivity reports, among others.

IoT sensors provide critical data on soil moisture, temperature, rainfall, and other environmental variables, which can be easily combined with global meteorological data and weather forecast, essential for precision agriculture. Satellite imaging provides insights into vegetation growth at the whole farm area, erosion, calamities, deforestation, CO_2 emissions, provides historical input for fertility maps, thus offering a holistic view of agricultural landscapes.

Cloud-native platforms and open APIs allow for a unified partner eco-system. The data hub serves as a versatile API platform designed to aggregate, normalize, and contextualize agricultural datasets from multiple providers. It supports a wide range of data types, including diverse crop data, weed data, sensor data, satellite imagery, and drone-captured images, enabling seamless integration and analysis. Built with extensibility in mind, the data hub ensures adaptability to evolving agricultural data needs.

Drones or UAVs, play a pivotal role in extending 5G coverage in agricultural and remote areas while performing critical tasks such as monitoring livestock, assessing biodiversity, detecting deforestation, identifying weeds, analyzing crop growth, and enabling remote spraying. Various types of agricultural drones are categorized in [22] and [23], including harvesting, spraying, conventional, mapping, and sensing UAVs.

However, these classifications lack a focus on addressing coverage issues.

To address this gap, we propose specific criteria that must be satisfied to develop an effective 5G coverage enhancement solution using drones tailored to agricultural applications. These criteria aim to ensure robust connectivity, operational efficiency, and scalability in supporting the diverse demands of modern agriculture:

- *Limited coverage area:* Providing 5G coverage using millimeter-wave technology in agricultural areas is challenging due to the short range of small cells (usually up to 500 meters), leading to higher deployment costs.
- *Drone-based base stations:* Drones equipped with 5G base stations can act as mobile coverage units, forming a chain to provide extended connectivity or landing in preassigned areas for targeted coverage during specific agricultural activities.
- *Airborne coverage:* For some agriculture use cases, drones can provide on-demand, flexible 5G coverage while airborne. Line-of-sight communication with fixed base stations ensures reliable backhaul, supporting latency-sensitive applications like real-time livestock monitoring or autonomous weeding or harvesting operations.
- *Dynamic deployment for cost efficiency:* Since coverage is needed only during specific periods (e.g., weeding, harvesting, crop health monitoring), drones can be redeployed to neighboring farms, enabling resource sharing and cost reductions across territories.
- *High-throughput and low-latency applications:* 5G-enabled drones can support bandwidth-intensive applications, such as real-time video streaming for animal or crop health analysis, remote equipment control (weeding, harvesting).
- *Integration with IoT ecosystems:* 5G drones can act as mobile hubs, connecting sensors and IoT devices deployed across farms, facilitating tasks like soil moisture analysis or smart irrigation.
- *AI-driven drone management:* Combining 5G with AI technologies enables intelligent drone management, such as automated path planning, weed detection, intelligent spraying, thus ensuring sustainability and cost-effectiveness.
- *Energy optimization:* Energy-efficient drone operations can extend their service duration, such as implementing energy-saving modes during idle times or solar-powered drones to enhance sustainability.
- *Extended operations:* Tethered drones, connected to a ground station for continuous power supply and backhaul communication, can provide long-duration coverage with minimal downtime, albeit at the cost of reduced mobility.
- *Multi-drone coordination:* Multiple drones can be coordinated to provide uninterrupted service by rotating active drones and recharging others, effectively overcoming flight time limitations.
- *Support for emergency connectivity:* Drones equipped with 5G can also provide temporary connectivity during emergencies, such as natural disasters or outages, ensuring uninterrupted communication and critical services.

These enhanced functionalities make 5G-enabled drones a transformative solution for delivering connectivity and enabling advanced digital applications in agricultural settings.

Efforts to create seamless technological experiences for farmers are further complicated by integration challenges. These arise from multiple standards-defining organizations (e.g., 3GPP, ETSI, GSMA, TM Forum), which result in varied protocols and frameworks; the proliferation of open-source initiatives with inconsistent compatibility; diverse third-party data services that are cumbersome to integrate; and variability in agricultural equipment interfaces, which hampers interoperability. The coexistence of multiple cloud platforms also creates integration difficulties, delaying the rollout of innovative services and revenue-generating opportunities. A holistic strategy is essential to overcome these integration challenges and unlock the full potential of modern agricultural technologies.

Our blueprint allows for the deployment of all these advanced equipment on the farm, thus optimizing the farmer‘s time, reducing labor cost and helping locally and globally with the UN sustainability goals [24], [25].

4. SELECTED SMART USE CASES

The following farming use cases are examples of the type of services enabled by the blueprint that the farmer can purchase and use. They cover the different aspects of crop and food cycle management, as well as animal health management.

4.1. Smart Weeding

Earlier studies in [26], [27], [28], [29], [30], [31] focused on automating weed control by improving real-time weed identification using different algorithms and optimizing the mechanical design of the weeding robot. The proposed crop-weed classification systems may be of different nature, applicable for different crops, but they demonstrate robust pixel-wise labeling of crops and weeds (include spatial information from image sequences).

Table 2
Requirements for selected use cases and the proposed solutions

Selected Use Cases:	smart weeding, smart harvesting	smart irrigation, water management	crop health monitoring, animal health monitoring
Requirements:	Automatic robots (UE) + HD cams High velocity (5 m/s), large data UL Ultralow latency UE←→MEC:10 ms AI/ML for classifying crops (form, size, color) AI/ML for classifying weeds (form, size, color) Satellite / drone imagery (weed map, crop growth), GPS navigation Closed-loop operation in real-time (< 200 ms)	Massive nr. of sensors (temp, humid) High range (~20 km) Low energy, easy installation Low bandwidth need UE ←→ CDC Smart irrigation equip (mob vs. fixed) AI/ML for smart irrig. algo's (@CDC) Satellite images with soil types & growth (nDVI), Weather forecast Field maps (variable irrigation zones) non-real-time decision (> 100 s)	HD cameras at selected locations on the farm HD cameras on drones for outdoor Coverage extension with chain of drones High BW need uplink UE ←→ MEC AI/ML/DL, computer vision algos (@MEC) GPS navigation Closed-loop operation in near-real-time (~1 s)
Solution Proposal:	5G-A mmW (private, on drones) & cloud, MEC + CDC + AI/ML & uRLLC + eMBB slice, asym. up/dw	LTE Cat 4, NB-IoT, LoRaWAN or 5G eRedCap 600-900 MHz & cloud, CDC + AI/ML & mMTC slice, sym.	5G-A mmW (private, on drones) & cloud, MEC + CDC + AI/ML/DL & eMBB slice, asym. up/dw
Abbreviations:	CDC: Central Data Computing eMBB: enhanced Mobile Broadband	5G-A mmW: millimeter Wave uRLLC: ultra-Reliable Low Latency Communication	5G eRedCap: e Reduced Capability mMTC: massive Machine Type Communication

In contrast, we propose transitioning decision-making intelligence to the network edge via 5G-A technology to reduce costs and improve the robustness of weeding robots. This approach enables the deployment of more advanced computer vision and machine learning algorithms, with inference results transmitted in real-time back to the robots through the same communication link. We implemented our approach.

In our first scenario, a smart robotic weeder connects to an edge server via 5G-A, enabling weed identification and targeted spraying as it moves at a constant speed along the seedbed. AI/ML algorithms control the process, with input from a camera mounted on the automatic weeder. Machine learning classifies, detects, and segments the objects to be detected by describing data features and extracting useful information from them. The system performs output actions such as spraying pesticide, physically extracting weeds, or using thermal methods. Key requirements include extremely low latency and high uplink throughput for 5G-A connectivity, as well as real-time AI/ML decision-making and control at the MEC. A preliminary training phase using relevant weed data was essential. Additional requirements for this use case are detailed in column one of Table 2 (multiple use cases may have the same requirements). Our approach significantly enhances efficiency while reducing the dependency on vulnerable hardware, such as GPUs on the weeder. The advent of 5G technology facilitates innovative operational schemes for robotics, allowing robots to execute a substantial portion of their tasks autonomously while delegating complex decision-making processes to the edge server.

In our second scenario, a specialized 5G-drone captures orthographic images from an altitude of 10 meters to detect weeds in a designated area prior to seeding, similarly, as in [32] and [33]. These images are transmitted in real-time to the edge server, where an AI/ML process identifies weed-infested micro-zones. The server then generates a file specifying the weed positions, which is sent back to the specialized drone. This drone subsequently applies a selected pesticide spraying method during its flight, ensuring precise and efficient weed management.

4.2. Crop Health Monitoring

Crop health monitoring, as demonstrated in [34] and [35], leverages drone-acquired images to assess plant health throughout growth stages using advanced AI-based semantic segmentation models such as U-Net and Explainable AI. This facilitates timely and appropriate interventions by farmers. In our catalyst example [25], a 5G-drone captures high-resolution images of potato fields from a height of 10 meters, which are then immediately pre-processed at the edge server and integrated into the farm management system. This technology effectively identifies stressed plants, optimizes resource use, aids in harvest scheduling, and is adaptable to other crops and environments.

Computer vision technologies enhance agricultural practices by analyzing leaf size, stem length, coloration, curvature, spotting, and tearing. When an ML algorithm detects anomalies, it triggers an alert on the monitoring dashboard. A 5G-drone can then be sent out for adequate actions. These advancements reduce labor-intensive tasks and time-consuming processes. Additionally, visual sensing and image recognition technologies enable tracking of crop health, monitoring maturity, and predicting yields [36], as well as the automatic detection of plant diseases and pests.

4.3. Smart Irrigation and Water Management

Smart irrigation systems harness the capabilities of 5G, IoT networks, soil moisture sensors, weather forecasts, AI/ML, and advanced irrigation equipment to optimize water usage for crops [37]. These systems analyze soil and weather data to develop predictive soil humidity models, which then activate precise control algorithms tailored to specific crop requirements. By ensuring optimal moisture levels with minimal water consumption, this approach achieves remarkable water efficiency [38]. The methodology adapts seamlessly to varying rain conditions, air humidity, weather patterns, crop types, and soil compositions. Its successful application in tomato fields, notably in Spain [39] and Ethiopia [40], demonstrates how technological innovation can address global water management challenges while promoting environmental sustainability.

To function effectively, cloud-based AI-controlled irrigation equipment requires various inputs, including data from soil, moisture, and temperature sensors; weather forecasts; crop and soil type information; and satellite or drone imagery of the fields. Using this data, the system can precisely activate irrigation mechanisms for the required duration and specific areas of the field, ensuring targeted water delivery.

The 5G-A connectivity is not mandatory for this use case, as there are many alternative wireless technologies (see Table 1), but can be used optionally in order to have just one unified technology, offering low-throughput connections, extended coverage for large distances using lower frequencies (600-900 MHz), and support for a massive number of sensors. While decision-making and control are AI-driven, they do not require real-time processing, which further supports scalability and resource efficiency.

The water management features of our system extend beyond irrigation control. By analyzing vegetation and water indices derived from satellite imagery, the system evaluates overall farm health. It provides actionable recommendations for crop placement and sensor deployment, generates soil moisture maps through integrated satellite and sensor data, and applies AI/ML models to these datasets to extract valuable insights. Ultimately, these insights inform irrigation strategies tailored to specific crops and environmental conditions, exemplifying the transformative potential of smart irrigation systems in global agriculture.

4.4. Smart Harvesting

Smart harvesting enables precise and efficient fruit or vegetable collection, ensuring optimal ripeness and quality, often during nighttime when conditions are ideal for harvesting [41], [42], [43]. Governed by AI/ML algorithms at the edge server, the system uses input from cameras on the harvester or 5G-enabled drones to gather real-time data. This allows the AI to identify and pick only ripe fruit while ensuring bruise-free harvesting, particularly for delicate crops like strawberries, spinach and lettuce, which require careful handling and timely collection. Detailed technical requirements for smart harvesting are outlined in Table 1. Not surprisingly, the connectivity requirements are very similar to those for smart weeding.

The process incorporates advanced features such as real-time ripeness evaluation and obstacle detection in crops like wheat, along with low-latency response mechanisms that optimize harvesting efficiency. The proposed solution also offers high harvesting capacity, especially important for time-sensitive crops like strawberries, and can operate up to 20 hours daily, with nighttime automation enhancing productivity.

The system may utilize 3D imaging technology to capture detailed data on fruits, vegetables, and plants, feeding AI models deployed at the network edge. Once the AI/ML/DL at the edge server determines that a fruit is ripe, it sends a real-time signal to the harvester to execute the picking action precisely. The system relies on 5G connectivity for ultra-low latency, high uplink throughput, and real-time AI decision-making on MEC, ensuring efficiency, precision, robustness, and scalability in modern agricultural applications. Additional inputs for the automatic harvester include field imagery from drones or satellites, depending on field size.

4.5. Food and Crop Storage Bin Monitoring

Smart IoT sensors can monitor the conditions within storage bins, such as temperature, humidity, and gas levels, to prevent spoilage and maintain the quality of stored crops [44]. Predictive analytics run locally on the MEC and can alert farmers and storage managers to potential issues, enabling timely intervention. Additionally, integration with automated ventilation and temperature control systems can optimize storage conditions in near-real time, further reducing spoilage and energy consumption. This synergy between IoT monitoring, AI-driven analytics, and automation enhances efficiency and sustainability in post-harvest management, it does not necessarily require real-time 5G connectivity, legacy sensor networks are sufficient.

To address the complexities of large-scale operations, modular IoT systems can be deployed, allowing flexible adaptation to different types of storage facilities, crop requirements, and geographic climates.

For instance, advanced sensor networks coupled with edge AI can dynamically prioritize bins requiring immediate attention. Challenges include the cost and scalability of installing IoT sensors. Furthermore, developing AI models capable of adapting to diverse and evolving environmental factors presents a significant technical challenge. Overcoming these hurdles will be crucial to making this solution universally applicable and economically viable.

4.6. Animal Health and Aquatic Life Monitoring

The animal health and livestock management use case leverage advanced technologies, including 5G, computer vision and AI/ML, to monitor the health, activity, nutrition, and growth of individual animals, while providing comprehensive insights at the herd level. State-of-the-art detection models such as You-Only-Look-Once (YOLO) and Vision-Transformer, enable real-time monitoring and analytics of critical livestock activities like feeding, calving, breeding detection, and predator alerts [45], [46].

These models, tailored to specific animal types (e.g., cattle, sheep, horses, goats, pigs, chickens and fishes) and environmental conditions, support the development of dynamic livestock management algorithms. These algorithms optimize operations such as timely feeding, efficient breeding assistance, and disease prevention measures. Near-real-time analytics further ensure rapid responses to issues, such as detecting when an animal has not consumed water for several hours, enabling farmers to take proactive actions to maintain herd health.

In our catalyst project [25] we used 5G-enabled cameras, animal tags, and sensors to provide precise tracking and monitoring over large or remote areas, transmitting high-resolution and reliable data about health and location. For instance, these systems enable ranchers to promptly identify and isolate sick animals, thereby mitigating the spread of infections within the herd. By integrating these technologies, farmers can significantly reduce labor costs, save time, and minimize losses while enhancing resource allocation and operational efficiency.

4.7. Additional Use Cases

Drones are becoming pivotal in agriculture, addressing critical needs throughout the farming lifecycle. During the pre-season phase, they facilitate land surveys, measurement, and topography assessment while assisting with water and soil management efforts, including regeneration. Optimal seedbed preparation also benefits from these capabilities. In the early season, drones enhance planting and sowing efficiency by monitoring stand spacing, counting, and quality [47]. Moving into mid-season, drones play a critical role in improving fertilization, monitoring crop growth to detect anomalies, and predicting yield potential [48], [49]. Late-season applications focus on harvesting, where drones contribute to biomass content analysis, crop maturity assessment, and soil conservation. They also aid in smart dispatch strategies for efficient crop transport. Post-season activities, such as sorting, classification, and storage optimization, are enhanced through AI-integrated systems, which enable precise crop categorization and logistics improvements in farm-to-consumer supply chains, including automated cleaning, grading, and packaging.

Supply chain transparency is another critical improvement, with blockchain technology ensuring traceability [50] and regulatory compliance across the food supply chain.

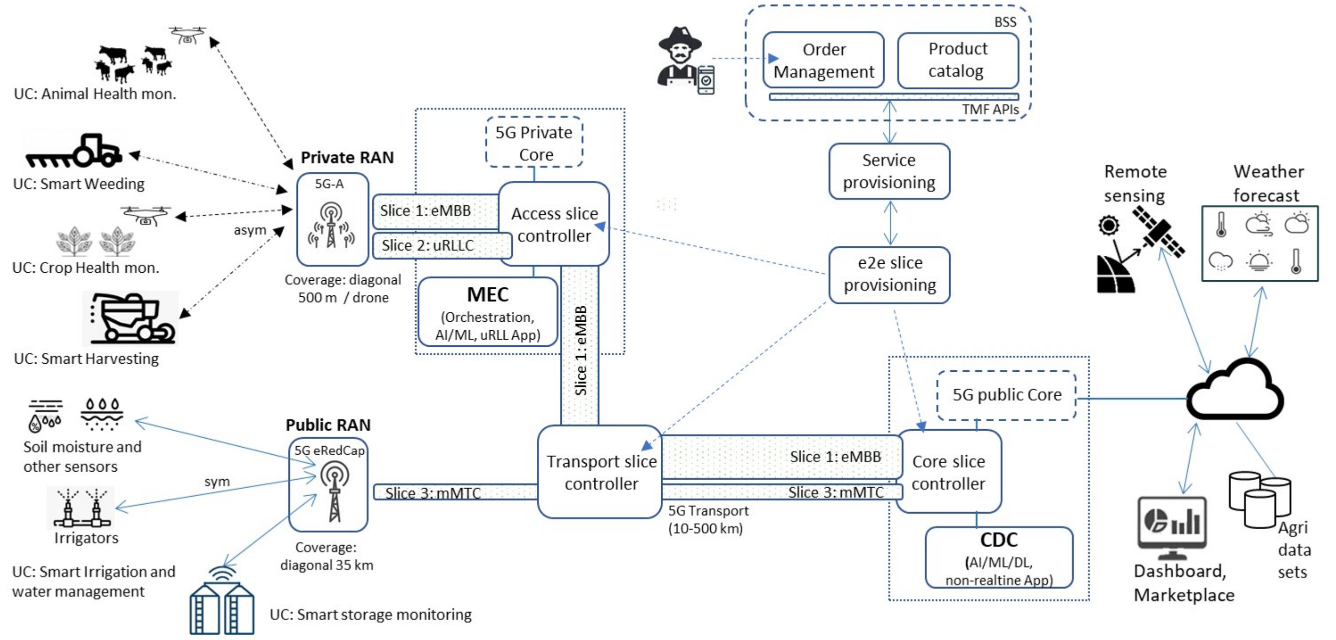
The scalability of these solutions ensures adaptability to diverse ranching environments, contributing to global sustainability and increased productivity.

5. SOLUTION DESCRIPTION

A very important element of the solution consists of 5G-drones in-a-chain, as described in Section 3, forming a scalable radio access network to address rural coverage gaps, connected to a 5G private core with MEC capabilities (as shown in Fig. 2). Each drone covers a 500-meter diagonal area and can be easily relocated to support other agricultural activities. Typically, the drones are stationary on the ground when not in flight, serving as mobile base stations while agricultural machinery such as tractors, harvesters, and agri robots operate within the coverage zone. By detecting handover activities, the drones autonomously relocate to the new area, maintaining continuous base station functionality. This approach results in significant energy savings as the drones are not airborne continuously. In some scenarios, drones could remain airborne for coverage, relying on line-of-sight communication with fixed base stations for backhaul, although flight time constraints may arise, potentially mitigated by using multiple drones or tethered drones. You may observe that the illustrated 5G transport segment in Fig. 2 can reach up to 500 km. The solution offers a cost-effective approach that unlocks new business opportunities for 5G private network service providers [48].

The 5G network, along with its associated business support systems (BSS) such as order management and product catalogs, enables subscribers to purchase agricultural use cases and their underlying technologies - network slicing, MEC, AI/ML/DL, robotics hardware/ software - via private networks designed for low-latency applications. A shift towards service-based open architecture integrates core network elements with northbound BSS through open APIs, enabling dynamic and flexible network service management to cater to diverse ecosystem requirements. By leveraging both public and private 5G networks, telecom operators can

Figure 2. Orchestration of network slices in public & private 5G networks



provide personalized agricultural solutions tailored to the needs of farmers across various stages of agriculture. Local MEC deployment is critical to achieving ultralow latencies for tasks such as weeding and harvesting, supported by seamless collaboration between edge and cloud infrastructures.

Network slicing, a cornerstone of 5G, creates multiple logical networks over a shared physical infrastructure, each optimized for specific use cases. Spanning end-to-end from devices to target applications, a network slice integrates access, transport, and core networks. Its effectiveness relies on the weakest link in the chain. In particular, access network slicing is pivotal, employing slice-specific resource allocation, scheduling, and traffic isolation mechanisms to meet performance requirements. Use cases for network slices are categorized as eMBB, uRLLC, and mMTC [51]. For example, animal and crop health monitoring require eMBB slices, smart weeding and harvesting rely on uRLLC slices, and applications like smart irrigation, water management and storage monitoring depend on mMTC slices, as illustrated in Fig. 2.

Transport slices interconnect endpoints with defined performance objectives, ensuring SLAs for end-to-end slices. While an orchestrator specifies endpoints and service-level goals, the transport slice controller manages underlying network resources to achieve these objectives. The core network acts as the anchor for 5G slices, managing device subscriptions and enabling UE network slice selection. Core slice attributes, such as coverage area, latency, throughput, and resource sharing levels, determine the configuration of the core network functions.

To realize the full potential of network slicing, CSPs must design and operate services spanning access, transport, and core domains, while actively engaging with the agricultural robotics ecosystem to ensure seamless connectivity.

A simplified business process, as illustrated in Fig. 3, provides an overview of the selected use cases, serving as a model for similar processes applicable to other agricultural scenarios.

5.1. Farmer Registration and UE Activation

- The farmer registers themselves and their agricultural robots (UEs) with the CSP's network via a dashboard, acquiring and assigning eSIM cards to each UE.
- Following the delivery and insertion of the eSIM cards into the UEs, the activation process begins. The UEs connect to the 5G network, identifying the required network parameters. If necessary, the nearest MEC service is located and assigned to the UE.
- Once activated, the UE enters an off-mode state and will reactivate before the start of the next scheduled activity during the season. This process supports intent-driven networking for business operations.

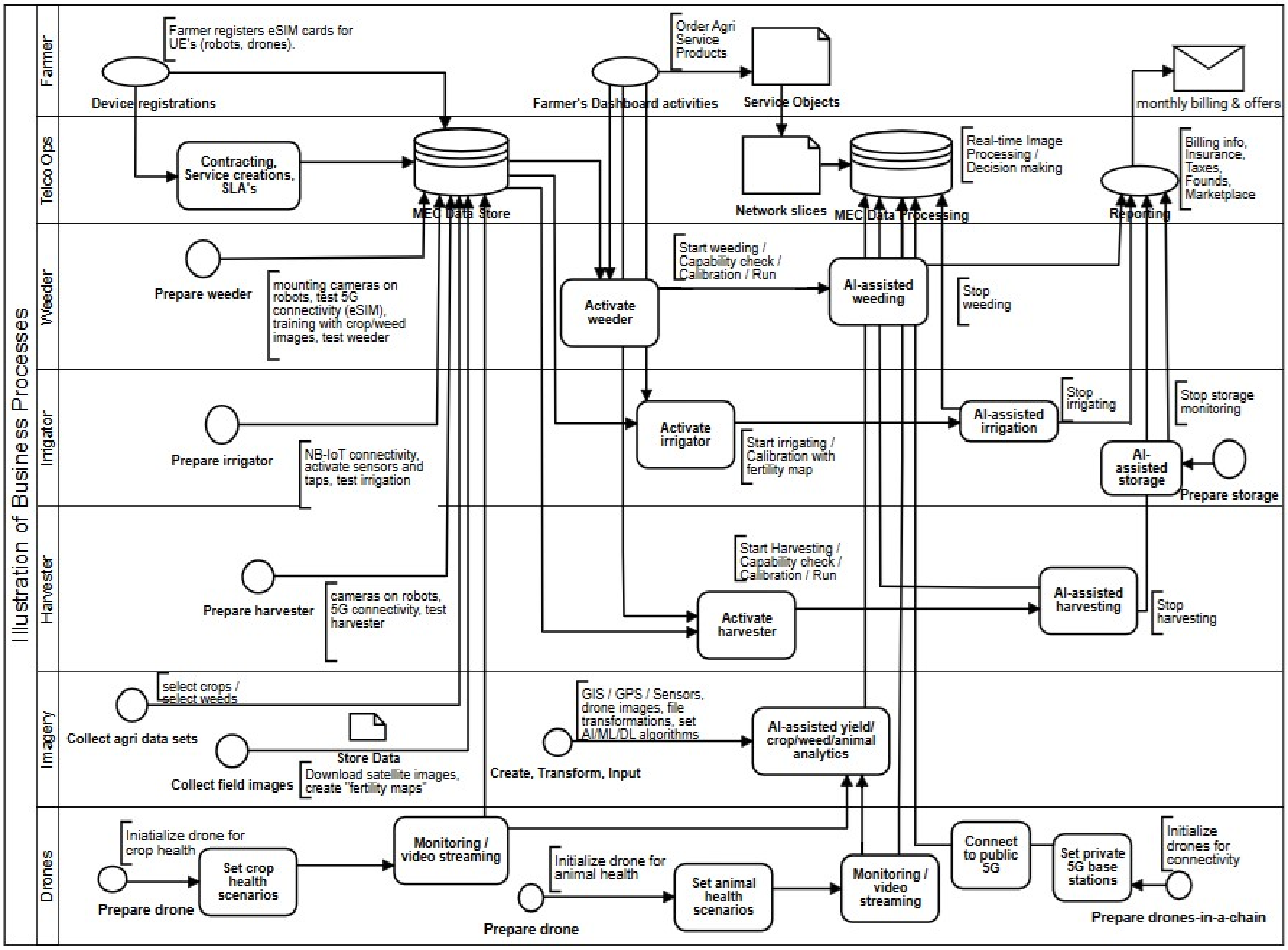


Figure 3. Farmer's and CSP's perspective (intent-driven activities) – a business process view

5.2. Service Request and Activation

- The farmer accesses the telecom operator's or CSP's order management platform via a dashboard to initiate the service request.
- The system verifies service availability, and the farmer specifies the desired Service Level Agreements (SLAs), effectively requesting network slices between UE and the 5G network.
- If required, a 5G-drone network is set up and activated to cover the designated area.
- Upon request, satellite- or drone-generated telemetry images and weather forecast data are integrated with the farmer's area of activity to enhance decision-making.
- Extensive agricultural datasets containing region- and season-specific images of crop and weed species support the AI/ML training process. If requested, pre-trained models for the selected crops or weeds are transferred to the assigned MEC for on-site processing.

5.3. Real-time Communication and Inference

- The farmer activates the agricultural robots and/or drones for tasks such as weeding or harvesting. Once the selected robot or drone reaches the designated field area, it begins its operation.
- Continuous real-time communication is established between the robot or drone and the MEC service, enabling instant decision-making via AI/ML algorithms. In some scenarios, drones equipped with 5G base stations are configured in a chain to extend real-time connectivity across large field areas effectively.
- Robots or drones transmit camera images to the AI/ML unit, where the data is processed to generate control commands with ultralow latency. For example, as a robot moves along a seedbed, it continuously transmits images of crops and weeds to the MEC. Based on AI/ML analysis, the system makes immediate decisions to selectively spray crops/weeds with precise amounts of pesticide/herbicide, minimizing

chemical usage. Similarly, during harvesting, decisions are made about whether to pick a fruit or crop based on its ripeness. This iterative process continues until the robot or drone completes its task and returns to the farm.

- Additional drones may be assigned for crop health monitoring, performing daily flights over selected areas with real-time connectivity and instant computer vision analytics to identify growth anomalies.

5.4. Non-real-time Communication and Inference

- The farmer accesses the platform to activate the irrigation system tailored to specific activity requirements such as region, season, soil type, fertility maps, crop type, and weather forecast. Through the platform, the farmer can monitor water usage, strategize irrigation plans, and evaluate drainage efficiency.
- Similarly, the farmer can activate and monitor the smart storage system tailored to specific crop or food types, such as humidity, temperature, gas concentration.
- The MEC aggregates sensor data (e.g., soil moisture, temperature) from the field regularly, such as hourly intervals, and integrates meteorological information (e.g., air temperature, rainfall, sunlight hours, weather forecasts). Using AI/ML algorithms, the system combines these inputs with fertility maps and crop water requirements to generate a watering schedule for the irrigation system or activate ventilation in the storage. Given the non-critical nature of these decisions, the accepted latency for decision-making can extend up to 100 seconds. The irrigation/storage system then operates taps as instructed by the MEC.
- On the dashboard, the farmer can visualize and monitor crop health and growth stages, facilitating early identification of leaks, diseases, and nutrient deficiencies. Tools for analyzing growth patterns, soil conditions, and precipitation assist in estimating yield and identifying opportunities to optimize fertilizer and pesticide use, reducing costs and environmental impact while maintaining productivity. Additionally, the farmer can evaluate damage caused by hail, disease, fire, extreme weather events, or other factors to assess financial impacts and streamline insurance claims.
- The farmer can deploy drones for crop and livestock management. These drones provide high-resolution RGB or multispectral data for applications such as counting, detection, behavior analysis, and feed availability monitoring. Drone data offers superior spatial and temporal resolution compared to satellite imagery and is more cost-effective than manned-aircraft surveys for equivalent data acquisition.

5.5. Billing, Invoicing and Marketplace Offering

- The CSP generates a periodic bill, typically on a monthly basis, summarizing the services utilized by the farmer. Details include itemized charges for each service, such as network slice usage, MEC processing, drone operations, and AI/ML analytics, with usage metrics like data transfer volume, time of use, and resources consumed for transparency.
- CSP may provide optional subscriptions for advanced AI/ML models, crop yield predictions, or weather pattern insights.
- CSP may partner with agricultural insurance providers to integrate crop damage assessments into the invoicing process, or share applicable tax benefits and government support programs.
- CSP provides a marketplace solution (logistics coordination, buyer/seller matching, and quality verification services) to streamline and expedite post-harvest processes, offering farmers easier access to resources and services needed after harvesting.

6. RESULTS AND DISCUSSIONS

This study focuses on agricultural use cases requiring ultra-low latency, with precision robotic weeding and smart harvesting as central applications. Precision weeding utilizes AI/ML/DL models at the MEC for real-time weed identification and targeted actions, such as pesticide or herbicide spraying, necessitating immediate feedback. Similarly, smart harvesting employs autonomous machines that leverage MEC-based AI-driven image recognition to identify ripe produce and handle crops delicately.

Table 3 presents the optimal attributes of network slices for selected agricultural use cases, demonstrating their alignment with eMBB, uRLLC, and mMTC categories. Typical values for latency [52], bidirectional asymmetrical throughput, mobility, density, and link QoS are defined to guide implementation. Notably, peak uplink speeds for key use cases, including those with guaranteed bit rate (GBR) capabilities, are 100 times higher than downlink speeds, deviating from traditional consumer network norms. Use cases such as weeding and harvesting demand isolated uRLLC slices with stringent latency requirements of approximately 10 milliseconds. Parameters such as potential service area, service time, and service availability ensure precise service ordering and provisioning by farmers.

Table 3
QoS attributes of our use case experiments for slice ordering and provisioning

Slice attributes	Use cases		
	Animal and crop health monitoring	Smart weeding and harvesting	Smart irrigation, storage mon
Type of slice	eMBB	uRLLC	mMTC
Latency (avg)	~ 1 s	~ 0.01 s	~ 100 s
PeakULspeed	~ 100 Mbps	~ 100 Mbps	~ 0.1 Mbps
PeakDLspeed	~ 1 Mbps	~ 1 Mbps	~ 0.1 Mbps
Service area	Regional	Local	Zonal
Service time	up to several hours	up to several days/weeks	UE battery life ~10y
UE mobility	~ 100 km/h	~ 20 km/h	~ 5 km/h
UE density	~ 1.000/km^2	~ 100/km^2	~ 10.000/km^2
Availability	99.99%	99.999%	99,9%
5G QoS ID*	72/56 GBR	82/19 delaycrit.GBR	5/10 non-GBR

*Source: 3GPP TS 23.501 V19.2.0 (2024-12), pp. 187-213.

Latency requirements were found to depend significantly on UE speed. Performance evaluations conducted using a prototype robot [25] assessed metrics such as time-to-detection and time-to-action under varying velocity conditions. The maximum UE speed is constrained by crop spacing (e.g., 20 cm in seedbeds), MEC computational capacity, and the uRLLC slice, which contributes 10 ms to the total round-trip time (RTT). Observed RTT values ranged between 50 and 200 ms (see Fig. 4). Similar results were obtained in [48]. Laboratory measurements and field trials at Olds College Farm in Canada validated these findings, showcasing the effectiveness of edge-based AI processing over 5G networks.

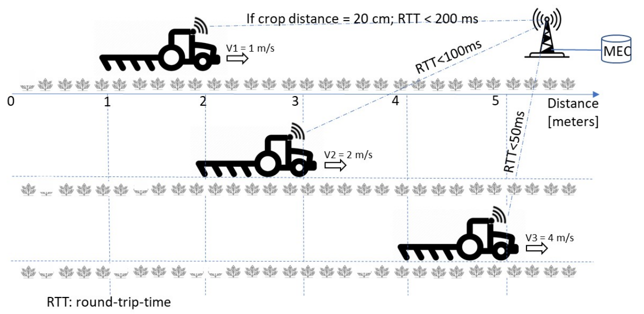


Figure 4. Illustration of low-latency requirements as a function of UE speed (smart weeder)

Moderate-speed UEs, such as robots operating at 1–2 m/s, can tolerate latency of 100–200 milliseconds for tasks like weeding or harvesting. High-speed UEs, including drones flying at 50 km/h, require latencies of 1–10 milliseconds for precise navigation and immediate actuation. Stationary or low-speed UEs, such as irrigation systems, allow higher latency thresholds of up to 100 seconds. Dynamic adaptation of network resources based on UE speed optimizes performance and efficiency, leveraging 5G-Advanced capabilities and network slicing.

Field trials demonstrated substantial efficiency gains: selective spraying operations reduced chemical usage by 20%, while AI-driven irrigation models decreased water consumption by 30% compared to traditional methods. Livestock management systems, supported by real-time alerts for feeding patterns and calving events, saved ranchers up to 50% of operational time.

Our 5G-connected robotic system incorporates a high-resolution camera that transmits images to the MEC via ultralow-latency network slices. ML algorithms classify plants using a database of over 1,000 annotated images, completing the detection-and-response cycle within 200 milliseconds and achieving 95% weed identification accuracy. Compared to manual weeding, which requires 20 hours per hectare, the robotic system processes the same area in three hours, significantly reducing labor and costs.

Field trials also revealed optimization opportunities. Doubling the robot’s speed (from 1 m/s to 2 m/s) reduced pesticide coverage on weeds by 10%. Lowering nozzle height from 60 cm to 30 cm further reduced pesticide use by 15% and weed coverage by 30%, underscoring the importance of precise mechanical configurations for optimal performance.

The findings emphasize the critical role of latency in agricultural robotics, particularly for real-time decision-making tasks. Comparative analyses confirm that 5G technologies outperform legacy systems in latency, throughput, and real-time responsiveness, aligning with recent research [50], [51], [53]. While tested in controlled environments, the proposed framework is adaptable to diverse agricultural scenarios, demonstrating significant potential for advancing precision farming practices.

6.1. Adaptability

In tropical regions, where rice and other water-intensive crops like sugarcane, cassava, and bananas are cultivated, 5G-enabled smart robotic technology can address unique challenges such as high weed density and fluctuating water levels. Autonomous robots equipped with specialized sensors can navigate flooded fields and dense vegetation to identify and target weeds precisely. Using real-time edge computing, the system adapts to local conditions, ensuring efficient herbicide application.

In arid and semi-arid regions, crops like olives, date palms, sorghum, and millet benefit from the application of 5G-based smart robotic systems. The framework’s ability to function in high temperatures and low humidity is supported by heat-tolerant sensors and drones. Real-time connectivity enables precise herbicide delivery and efficient energy use, critical in regions with limited resources. The technology facilitates soil moisture preservation and weed control.

In temperate climates, the 5G-enabled framework supports a wide range of crops, including wheat, maize, potatoes, cabbage, rapeseed, sunflower, sugar beets, and grapes. Smart robots leverage advanced AI models to differentiate crops from weeds, even in early growth stages. They adapt to varying field layouts, navigating uneven terrains, from tightly spaced potato rows to sprawling sunflower fields, using real-time data for navigation and precision application.

6.2. Scalability Explained Easy with Use Cases

Device Density: Assess the network's ability to support high device density for rice fields with submersible water sensors and drones monitoring canopy health. Measure support for wheat, maize, and vineyard systems where multiple robots, drones, and sensors operate simultaneously. Evaluate density for sparse yet critical devices used in olive groves or pomegranate farms.

Network Throughput: Measure the throughput for drones transmitting high-resolution images of pest outbreaks. Test simultaneous video streams from vineyard-monitoring drones and edge-based weed detection for maize and potato farms. Evaluate throughput for satellite-assisted irrigation monitoring and olive yield mapping.

Latency and Reliability: Ensure ultra-low latency for real-time feedback to autonomous harvesting robots in rice fields. Validate latency for robot-driven harvesting in vineyards or cabbage fields, where precision timing is critical. Test latency for non-real-time alerts on soil moisture levels and wind-driven pest movement across orchards.

Dynamic Resource Allocation: Evaluate network slicing for uRLLC, eMBB or uRLLC for all use cases [54].

Edge Computing Scalability: Measure the MEC's capacity to process AI models, evaluate scalability for image processing and real-time crop/weed classification. Assess edge capacity for multispectral analysis for ripeness evaluation.

Energy Efficiency: Test energy efficiency of solar-powered sensors and drones monitoring crop health. Monitor energy consumption for robotic harvesters working for extended hours.

Geographical Coverage and Mobility Support: Ensure seamless coverage across waterlogged terrains. Validate coverage for rolling hills in vineyards and vast flatlands in maize farms. Test mobility support for autonomous vehicles in expansive, sparsely connected olive orchards.

Interoperability and Extensibility: Evaluate how easily the 5G system integrates with legacy irrigation systems. Assess interoperability with diverse machinery used in wheat and potato harvesting. Ensure compatibility with satellite-based weather prediction systems and local groundwater monitoring infrastructure.

Cost-Effectiveness: Measure cost per hectare for deploying 5G-connected drones and sensors. Analyze costs for robot fleets and sensor networks across fields. Calculate costs for deploying low-power, solar-assisted IoT devices for water-efficient cultivation.

By adapting these measurements to the diverse agricultural practices and climatic conditions, the scalability of 5G networks can be holistically assessed and optimized for global application.

6.3. Economic Viability for Smaller Farms

The economic viability of the 5G system for smaller farms hinges on its ability to reduce operational costs while boosting productivity. By leveraging network slicing, MEC, and IoT-enabled devices, smaller farms can adopt precision agriculture tools tailored to their needs without heavy upfront investments in hardware. For instance, shared drone services and scalable edge processing can reduce equipment costs. Additionally, savings on inputs like water and chemicals due to precise targeting, along with labor cost reductions through automation, offset the initial setup costs. Intent-driven models, such as Network-as-a-Service, further enhance affordability, making advanced 5G technologies accessible even to small-scale farmers globally.

7. CONCLUSIONS

This applied research study introduced a scalable and innovative framework for integrating 5G-Advanced networks with AI-driven IoT technologies, tailored to address the challenges and demands of modern agriculture. The framework employs advanced methodologies, including 5G-drone chains for extended coverage, intent-based farming supported by network slicing, and the migration of computational workloads from user equipment to edge servers. By overcoming traditional barriers such as high implementation costs and limited scalability, the proposed approach leverages intelligent edge infrastructure to make precision agriculture accessible to farms of varying scales and capacities.

By addressing challenges of latency, resource efficiency, and scalability, the framework demonstrates measurable benefits such as reduced water and chemical usage, enhanced crop yields, and significant labor cost savings, making it economically viable even for smaller farms. Enhanced rural connectivity fosters real-time decision-making, traceability, and the adoption of sustainable supply-chain practices, directly aligning with United Nations Sustainable Development Goals (SDGs) related to food security, clean energy, climate action, and rural development. Quantifiable impacts include reductions in water usage, greenhouse gas emissions, pesticide application, and energy consumption, alongside advancements in carbon sequestration and CO_2 data collection. These achievements underscore the transformative potential of integrating 5G technologies and AI in agricultural operations.

Although designed with agricultural applications in mind, the principles and methodologies of this framework are broadly applicable across industries seeking sustainable solutions through advanced technologies. Future research will focus on further refining these technologies for broader applications and expanding their implementation in real-world settings to promote food security and rural development worldwide. By advancing these goals, the framework sets the foundation for a more sustainable and efficient technological ecosystem across multiple sectors.

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Any views expressed in this paper are those of the authors and do not necessarily reflect the views of their companies.

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