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AGRARIAN: A Hybrid AI-Driven Architecture for Smart Agriculture

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Abstract: Modern agriculture is increasingly challenged by the need for scalable, sustainable, and connectivity-resilient digital solutions. While existing smart farming platforms offer valuable insights, they often rely heavily on centralized cloud infrastructure, which can be impractical in rural or remote settings. To address this gap, this paper presents AGRARIAN, a hybrid AI-driven architecture that combines IoT sensor networks, UAV-based monitoring, satellite connectivity, and edge-cloud computing to deliver real-time, adaptive agricultural intelligence. AGRARIAN supports a modular and interoperable architecture structured across four layers—Sensor, Network, Data Processing, and Application—enabling flexible deployment in diverse use cases such as precision irrigation, livestock monitoring, and pest forecasting. A key innovation lies in its localized edge processing and federated AI models, which reduce reliance on continuous cloud access while maintaining analytical performance. Pilot scenarios demonstrate the system's ability to provide timely, context-aware decision support, enhancing both operational efficiency and digital inclusion for farmers. AGRARIAN offers a robust and scalable pathway for advancing autonomous, sustainable, and connected farming systems.

Keywords: smart agriculture; AI-driven decision support systems; precision farming

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1. Introduction

The global agricultural sector is undergoing a fundamental transformation driven by rapid advancements in digital technologies, artificial intelligence (AI), and the Internet of Things (IoT). These innovations are reshaping traditional farming methods, optimizing resource efficiency, productivity, and sustainability in response to increasing food demand and climate change challenges. The European Commission has emphasized that digitalization in agriculture is a critical component for improving competitiveness, fostering sustainable practices, and ensuring food security in the European Union (EU) and beyond [1].

Modern agricultural systems are increasingly relying on connected infrastructures, including smart sensors, AI-driven decision-making tools, and cloud-based agricultural platforms, to enhance real-time monitoring, automated farm management, and precision agriculture techniques. This transition aligns with the Agriculture 4.0 paradigm, which integrates big data analytics, robotics, and advanced network communication protocols to optimize agricultural operations [2].

The Common Agricultural Policy (CAP) has been a cornerstone of the EU's agricultural strategy, focusing on sustainability, productivity, and the socio-economic well-being of farmers [3]. Recent CAP Strategic Plans for 2023–2027 emphasize the role of digital tools, AI, and IoT in improving decision-making for farmers while promoting climate-resilient agricultural practices [4]. Additionally, EU-backed initiatives on smart farming provide targeted support for the adoption of cloud computing, AI-driven analytics, and blockchain technologies to ensure traceable, transparent, and efficient agricultural supply chains [5]. Despite the potential benefits of precision farming technologies, many farmers still face economic and technical barriers to adoption. According to Eurostat, agricultural labor input in the EU has continued to decline, highlighting the need for automation and smart agricultural solutions to compensate for workforce shortages [6–8].

Several international research initiatives from countries like Israel and China have made substantial progress in smart agriculture. Israel has been a leader in sensor-based drip irrigation systems, leveraging local edge controllers to manage water efficiency in arid environments. Chinese efforts have advanced in areas such as UAV-enabled field monitoring, blockchain-integrated supply chains, and remote sensing for pest management. These technologies are often domain-specific and vertically optimized, addressing critical challenges such as irrigation, crop health, and traceability. However, they tend to rely on centralized architectures, which can be constrained by connectivity gaps or lack of adaptability in remote rural contexts.

AGRARIAN addresses a clear research and deployment gap by offering a modular, horizontally and vertically scalable architecture that unifies edge AI, federated learning, and hybrid connectivity (5G/LEO satellites) within a single framework. Unlike traditional siloed models, AGRARIAN is designed to support simultaneous, real-time operations across layers—from sensor data capture to AI-driven decision support—while optimizing for energy use, latency, and interoperability. This capability is particularly important for rural deployments with intermittent connectivity, making AGRARIAN adaptable where centralized models fall short. Its layered design also supports dynamic resource allocation via slicing, enabling precision agriculture to scale across varied operational environments with different infrastructure constraints.

Driven by the challenges of climate change, resource constraints, and the growing demand for sustainable food production, the AGRARIAN architecture introduces a hybrid AI-driven framework that seamlessly integrates IoT sensors, UAVs, satellite-based remote sensing, edge computing, and AI-powered decision support systems (DSS) to transform precision farming, livestock management, and agricultural sustainability. Unlike conventional systems reliant on centralized cloud processing, AGRARIAN decentralizes data analysis through edge AI and federated learning, significantly reducing latency, bandwidth consumption, and dependency on continuous connectivity. Its four-layered structure—Sensor, Network, Data Processing, and Application Layers—ensures a scalable and modular system where multimodal sensors capture real-time environmental, soil, and livestock data, processed through AI-driven analytics at the edge or in the cloud.

The structure of this paper is organized as follows: Section 2 presents an overview of related technologies, focusing on IoT-based irrigation systems, AI-driven crop protection, decision support systems (DSS), and satellite-enabled precision agriculture. Section 3 introduces the AGRARIAN system architecture, detailing its horizontal and vertical architectural models, along with the integration of edge computing, hybrid networking, and cloud-based AI analytics, an in-depth analysis of the four-layered structure of AGRARIAN, comprising the sensor, network, data processing, and application layers, describing their role, interaction, and impact on smart agriculture. Finally, Section 4 concludes with key findings, potential limitations, and future research directions in hybrid AI-driven agricultural frameworks.

2. Related Technologies

The integration of Internet of Things (IoT) devices and 5G networks is transforming smart irrigation management by enabling real-time monitoring and automated water control. IoT-based sensors, combined with cloud-based decision support systems (DSS), allow precise irrigation scheduling based on soil moisture levels, weather conditions, and crop water demand. The use of 5G connectivity enhances data transmission speed, ensuring low-latency, AI-powered water management solutions that contribute to efficient water resource allocation and climate resilience [9]. Beyond irrigation, DSS also plays a critical role in agrarian policy-making and economic planning, as seen in Ukraine, where data-driven accounting tools are used to align agricultural strategies with European integration frameworks. These systems analyze farm productivity metrics, subsidy allocations, and rural development trends to optimize policy interventions [10].

2.1. AI for Crop Protection and Environmental Monitoring

AI-based decision support technologies are also reshaping crop protection and disease management. Modern deep learning models, when combined with satellite imagery and IoT sensors, enable real-time disease prediction and early detection, reducing the dependency on excessive pesticide use. AI-driven DSS can process historical weather data, pathogen distribution models, and soil health indicators to provide targeted, proactive recommendations for farmers [11]. Satellite technology, particularly CubeSats and GIS-based remote sensing, is revolutionizing precision agriculture by offering high-resolution environmental monitoring. These small satellites provide frequent, real-time imaging, allowing farmers to track crop health, soil moisture levels, and land-use changes, which are then integrated into DSS platforms to facilitate data-driven decision-making for sustainable farming [12].

2.2. DSS for Water Resource and Livestock Management

Water management in agriculture remains a pressing challenge, and DSS frameworks are being developed to guide groundwater resource allocation, especially in drought-prone regions. AI-powered decision tools enable multi-stakeholder collaboration, integrating hydrological models, water demand forecasting, and climate impact assessments to ensure sustainable irrigation practices [13]. In precision livestock farming, AI-driven DSS are being deployed to monitor animal welfare, detect diseases, and optimize feed efficiency. Machine vision, biometric sensors, and predictive analytics allow for real-time tracking of livestock health, reducing operational costs and improving farm productivity [14]. These advancements are not only enhancing individual farm operations but are also influencing renewable energy production in agriculture. DSS frameworks are now used for biogas facility planning, optimizing locations based on geospatial data, waste production metrics, and sustainability indicators. This application supports circular bioeconomy models, where agricultural waste is converted into biofuels and organic fertilizers, reducing carbon footprints and environmental impact [15].

2.3. Circular Bioeconomy and Smart Supply Chains

Decision support technologies also play a crucial role in circular bioeconomy strategies, ensuring efficient resource recycling and sustainable food production systems. AI-powered DSS facilitates agricultural waste management by optimizing the bioconversion of crop residues into bioenergy and minimizing resource wastage [16]. Recent developments in digital agriculture and AI-driven decision systems show that fine-tuned natural language processing (NLP) models outperform traditional chatbot-based farm management solutions. These AI-powered DSS provide context-aware recommendations for crop management, pest control, and supply chain logistics, improving farm productivity and sustainability [17]. Additionally, digital technologies are increasingly being commercialized for nature conservation and ecosystem service provisioning in agriculture. By integrating remote sensing, AI-based environmental modeling, and cloud-based analytics, these tools help farmers balance economic profitability with ecological preservation, ensuring that agriculture remains both productive and environmentally responsible [18].

2.4. Convergence of Digital Agriculture Technologies

As agriculture continues to evolve towards a data-driven, digitally connected ecosystem, the integration of AI, IoT, and DSS technologies is becoming essential. From smart irrigation management and CubeSat-based environmental monitoring to precision livestock farming and biogas facility optimization, DSS is empowering farmers and policymakers with real-time insights for sustainable decision-making. The convergence of edge computing, cloud-based AI analytics, and stakeholder collaboration is paving the way for a resilient, efficient, and sustainable agricultural future.

Enhancing digital infrastructure and hybrid communication technologies is, therefore, a key priority in ensuring widespread accessibility to smart farming solutions across Europe.

2.5. Challenges and Infrastructure Considerations

While digital agriculture offers significant opportunities for growth and sustainability, several challenges must be addressed:

- Connectivity Gaps: Many rural farming areas suffer from limited broadband access, restricting the adoption of real-time IoT monitoring and AI-driven decision systems [19].
- Interoperability Issues: The diverse range of agricultural IoT devices, cloud platforms, and AI models creates integration challenges, requiring standardized data exchange protocols [20].
- Data Privacy and Security: The sensitive nature of farm data necessitates robust cybersecurity frameworks, including secure data transmission protocols like NETCONF and YANG [21,22].

Scalability and Computational Demand: AI-driven edge computing is increasingly being explored to reduce the burden on cloud infrastructure, enabling localized, real-time data processing for smart agriculture [23].

To address these challenges, next-generation networking protocols such as Recursive InterNetwork Architecture (RINA) are being explored to replace traditional IP-based architectures, improving network scalability, data security, and real-time processing capabilities for large-scale agricultural IoT systems [24].

2.6. Edge Computing and Federated AI for Real-Time Farming

A critical technological enabler for precision farming is edge computing, which facilitates real-time data analysis at the farm level without the need for continuous cloud connectivity [23]. By deploying localized AI models on edge devices, UAVs (drones), and satellite nodes, latency is minimized, bandwidth consumption is reduced, and real-time decision-making is enhanced. Recent studies suggest that federated learning and AI-driven edge computing can significantly improve agricultural supply chain efficiency, reducing costs and optimizing farm management strategies [23].

3. AGRARIAN Architecture

The AGRARIAN architecture, Figure 1, is designed to provide a robust, scalable, and intelligent agricultural technology ecosystem, integrating sensor networks, AI-driven decision support, hybrid communication networks, and cloud-based analytics. This system is structured into multiple layers to ensure seamless functionality, interoperability, and efficient data flow between different components. The architecture is conceptualized through two complementary views: the horizontal and vertical architectures, each detailing the organization of system elements and their interactions.

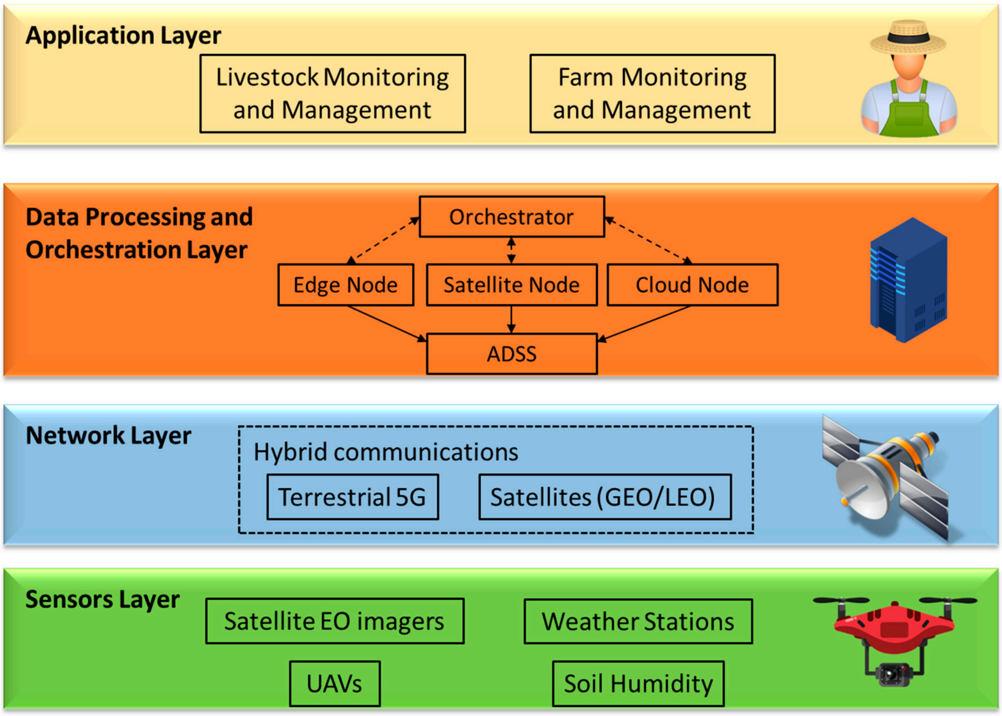

Figure 1. AGRARIAN High-Level Architecture: Integrating IoT, Edge AI, and Hybrid 5G Connectivity for Smart Agriculture.

The AGRARIAN architecture is designed to support precision farming, livestock monitoring, vineyard management, and environmental sustainability. It is composed of multiple interconnected layers that facilitate sensor data acquisition, edge computing, satellite communications, and AI-driven analytics. The horizontal architecture provides an end-to-end view of how different components interact, while the vertical architecture focuses on the service-oriented structure of the system. The horizontal architecture emphasizes the interaction between the customer portal, decision support systems (ADSS), infrastructure, and external data sources. The vertical architecture, on the other hand, categorizes these functionalities into four major layers: Sensor Layer, Network Layer, Data Processing Layer, and Application Layer.

AGRARIAN is currently being evaluated in pilot deployments across vineyard ecosystems and livestock farms, where real-world feedback has helped fine-tune energy management, model accuracy, and connectivity handling. These pilots validate AGRARIAN's layered operation: sensor layer (uRLLC) for fast data capture, network layer for hybrid 5G-satellite backhaul, processing layer (eMBB slicing) for model inference, and application layer for user interaction and alerts. The system also includes API interfaces for future integration with farm machinery, supporting ISOBUS and OPC UA standards. This ensures that AGRARIAN is not only a theoretical model but a deployable, extensible solution for autonomous, sustainable agriculture.

Application Layer

The Application Layer, Figure 2, provides user-facing tools that allow farmers, policymakers, and researchers to interact with the AGRARIAN system, offering AI-powered agricultural insights, decision support, and precision farming applications.

- Agricultural Decision Support System (ADSS): Analyzes sensor, satellite, and UAV data to provide actionable insights on crop health, livestock management, and irrigation scheduling.
- Livestock Monitoring and Anomaly Detection: Uses AI-driven video analytics and GPS tracking to identify anomalous animal behavior, potential health risks, and missing livestock.
- Crop Growth and Yield Forecasting: Predicts crop productivity, pest risks, and optimal harvesting times based on machine learning algorithms and real-time environmental data.
- Smart Irrigation and Water Management: Uses soil moisture analytics, weather forecasts, and AI-based optimization to ensure efficient water usage and minimize waste.
- Disease and Pest Alert Systems: AI models process multispectral and SAR data to predict disease outbreaks and recommend timely interventions.
- Supply Chain Traceability and Food Safety: Blockchain-enabled traceability solutions ensure transparent farm-to-market logistics, improving food safety and regulatory compliance.

By integrating advanced analytics, real-time alerts, and predictive modeling, this layer empowers users with intelligent decision-making tools for sustainable and efficient farming.

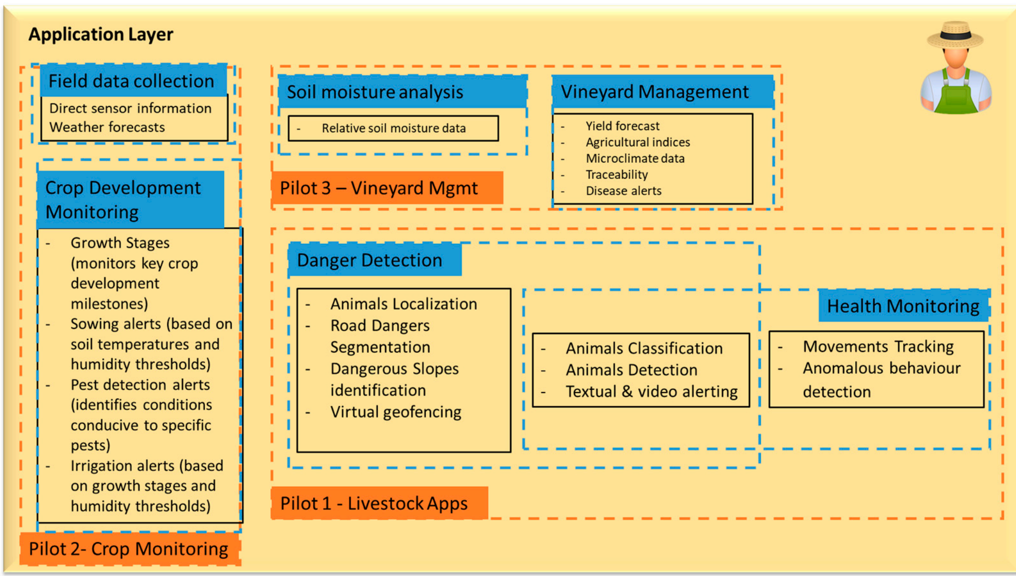

Figure 2. Application layer.

Data Processing and Orchestration Layer

The Data Processing Layer, Figure 3, acts as the computational hub of the AGRARIAN system, processing, analyzing, and distributing agricultural data across the network. This layer leverages edge computing, cloud processing, and AI-based analytics to extract meaningful insights from raw sensor data.

- Edge AI and Federated Learning: Distributed AI models are deployed on satellites, UAVs, and farm-based edge nodes, allowing real-time inference for disease detection, irrigation control, and crop monitoring.
- CI/CD Pipelines for AI Model Deployment: Continuous integration and deployment pipelines ensure real-time AI model updates for improved analytics and decision-making.
- Cloud-Native Orchestration (Kubernetes, KubeEdge, and K3s): Supports scalable, fault-tolerant, and distributed AI computing for precision farming applications.
- Satellite AI Processing: Enables onboard AI inference on CubeSats, reducing latency and bandwidth consumption while providing actionable insights directly from space-based monitoring.
- Data Storage and Integration with External Sources: Ensures secure, efficient storage and retrieval of environmental, livestock, and field data, integrating external climate databases, weather APIs, and agricultural knowledge repositories.

By leveraging advanced AI and edge computing technologies, this layer enhances decision-making efficiency and scalability.

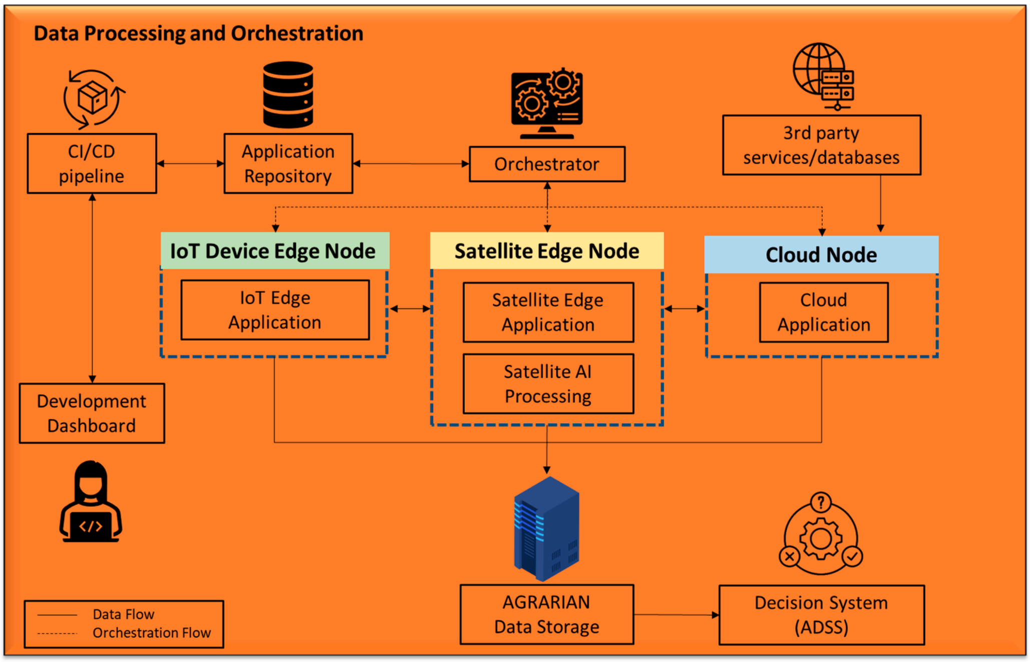

Figure 3. Data Processing and Orchestration layer.

The AGRARIAN architecture incorporates various methodological approaches—such as real-time edge AI, federated learning, and satellite-based inference—not as isolated innovations but as components selected and positioned according to specific agricultural use cases and their corresponding feasibility and problem-solving impact. It is acknowledged that not all agricultural operations require real-time decision-making. For example, strategic planning tasks like yield forecasting or soil nutrient mapping are typically tolerant of batch processing and delayed analytics. However, certain scenarios do benefit from real-time or near-real-time responsiveness. These include livestock anomaly detection (e.g., animal distress or escape), localized irrigation control during heatwaves, and pest outbreak alerts, where immediate data-driven insights can significantly reduce risks or losses. In such contexts, AGRARIAN's edge computing and low-latency satellite links offer value by enabling timely interventions without reliance on centralized cloud infrastructures. The architecture supports hybrid deployment models that allow stakeholders to scale computational resources and analytical intensity according to operational context and economic viability. By not assuming a one-size-fits-all requirement for real-time processing, AGRARIAN is designed with a flexible orchestration layer that balances real-time capability with practical feasibility and cost-effectiveness across scales and farming profiles.

Network Layer

The Network Layer, Figure 4, enables seamless connectivity across all AGRARIAN components, ensuring reliable communication between sensors, computing nodes, and cloud-based systems. It integrates terrestrial and satellite communication networks to provide uninterrupted connectivity in remote agricultural areas.

- 5G-Based Communication: Provides high-speed, low-latency connectivity for real-time sensor data transmission and remote farm monitoring.
- Hybrid Satellite Communications (LEO and GEO): LEO satellites facilitate low-latency broadband access, while GEO satellites provide continuous global coverage.
- Edge Network Infrastructure: Supports real-time AI model deployment and inference at the farm level, reducing dependency on centralized cloud computing.
- Delay-Tolerant Networking (DTN) and IoT Protocols: Allow efficient data transmission in rural and disconnected environments, ensuring that time-sensitive agricultural data is not lost.
- Ground Network Infrastructure: Includes 5G base stations, ground terminals, and IoT gateways, allowing seamless integration of AGRARIAN's sensor networks with cloud-based decision support systems.

This layer ensures uninterrupted connectivity, which is essential for real-time agricultural monitoring and automated farming solutions.

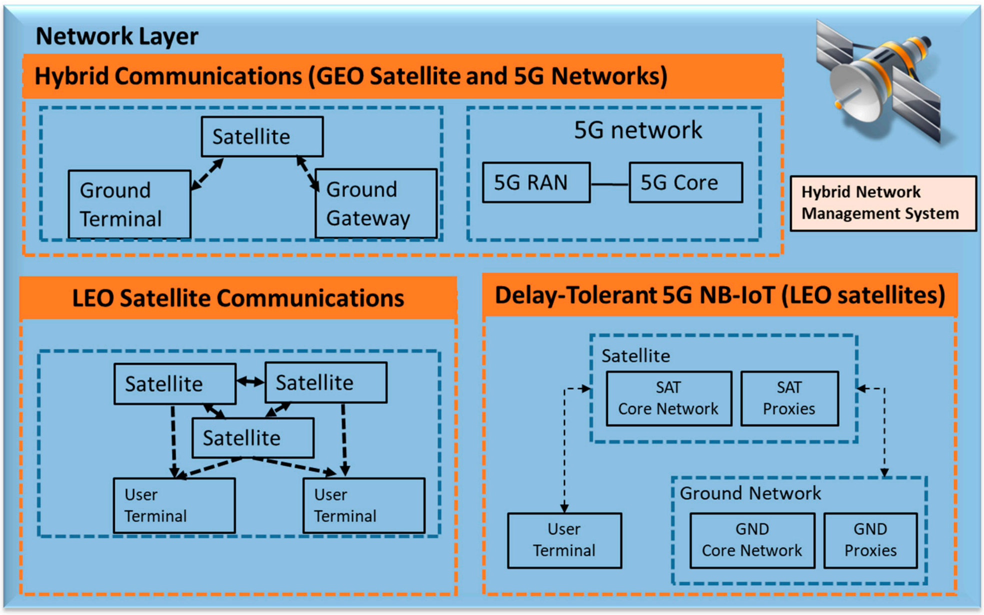

Figure 4. Network layer.

Sensor Layer

The Sensor Layer, Figure 5, is the foundation of the AGRARIAN system, comprising various data acquisition technologies that capture environmental, soil, and livestock data. These sensors are deployed in situ, on UAVs, and in satellite-based observation systems, ensuring continuous real-time monitoring of agricultural parameters.

- IoT and Ground Sensors: Measure soil moisture, temperature, air humidity, and precipitation, providing critical data for precision irrigation and crop health analysis.

- UAV-Based Sensors: Equipped with multispectral cameras, RGB cameras, and real-time kinematic (RTK) sensors to provide high-resolution field images and topographical mapping.
- Weather and Climate Stations: Monitor meteorological parameters such as wind speed, temperature, solar radiation, and frost prediction, supporting weather-based agricultural decision-making.
- Satellite Earth Observation (EO) Systems: Utilize Sentinel-based multispectral imaging and Synthetic Aperture Radar (SAR) to provide wide-area, high-resolution monitoring for crop health, soil moisture levels, and yield estimation.
- Livestock Tracking Devices: Sensors embedded in wearables and drones to track animal movement, health status, and anomaly detection.

This layer ensures real-time, accurate data collection for informed decision-making within the AGRARIAN ecosystem.

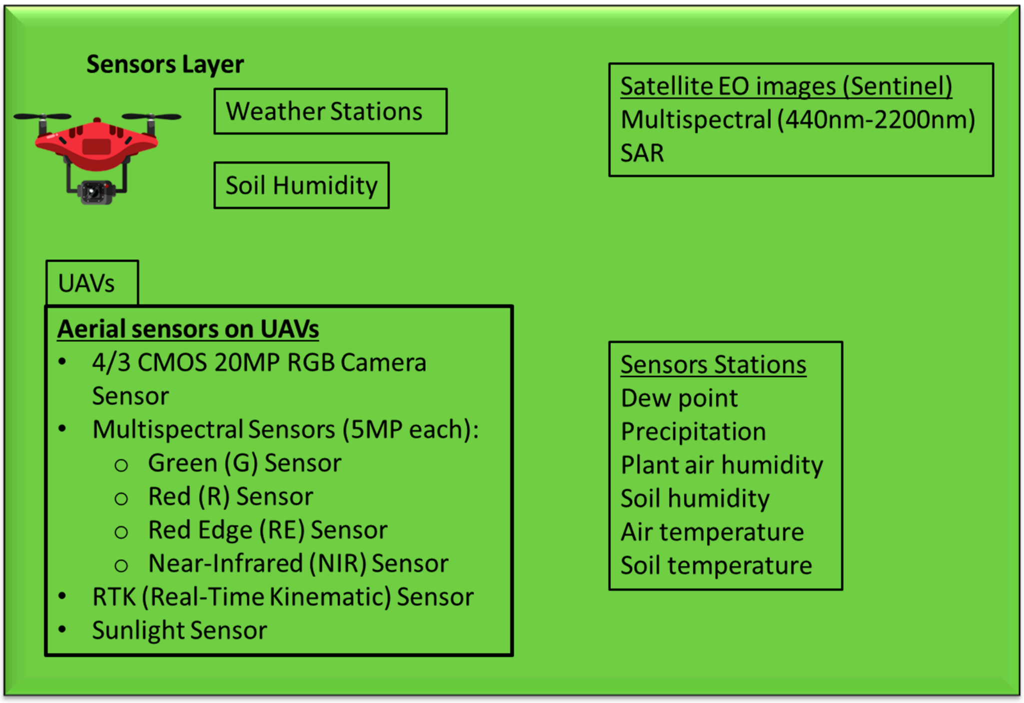

Figure 5. Sensors layer.

This layer ensures real-time, accurate data collection for informed decision-making within the AGRARIAN ecosystem by integrating a diverse range of sensors deployed across agricultural fields, UAVs, and satellites. Ground-based IoT sensors continuously monitor soil moisture, temperature, humidity, and nutrient levels, providing granular insights into crop health and water needs. UAV-mounted multispectral and thermal sensors capture high-resolution imagery, detecting early signs of crop stress, pest infestations, and irrigation inefficiencies. Weather and climate stations collect atmospheric data, including wind speed, solar radiation, precipitation, and frost risk, enabling microclimate analysis for precision farming. Satellite Earth Observation (EO) systems, leveraging multispectral imaging (Sentinel) and Synthetic Aperture Radar (SAR), offer wide-area crop monitoring, soil moisture assessments, and predictive yield modeling, even under cloud cover and adverse weather conditions. For livestock applications, wearable biometric sensors track movement patterns, body temperature, and feeding behavior, facilitating real-time animal health monitoring and anomaly detection. By ensuring seamless integration of these diverse sensing technologies, the AGRARIAN architecture enables data-driven, AI-enhanced decision-making, fostering sustainable resource management and improved farm productivity.

While the AGRARIAN architecture provides a comprehensive and modular framework for smart agriculture, it is important to critically reflect on its current scope and future integration opportunities. One notable area of expansion involves the direct interfacing of AGRARIAN with agricultural machinery, such as autonomous tractors, robotic sprayers, and harvesters. Although the present architecture primarily focuses on sensor networks, edge/cloud analytics, and decision support, its design is intentionally modular, with API-based interoperability layers that support future integration with smart machinery systems. Technologies such as ISOBUS, MQTT, and OPC UA are being considered for implementing bidirectional communication between the decision support system (ADSS) and farm equipment, enabling automated actuation based on AI-driven recommendations. Furthermore, AGRARIAN's architecture supports future expansion through control-layer protocols and real-time machine interfaces, establishing the foundation for intelligent automation. Implementation-wise, the architecture is already being validated in pilot environments—including livestock farms, vineyards, and field crop settings—where sensor deployment, satellite connectivity, and edge AI models are tested for latency, scalability, and usability. These real-world testbeds are key to evaluating AGRARIAN's readiness for broader deployment and demonstrating its potential to connect directly with autonomous agricultural machinery, enhancing operational efficiency and promoting end-to-end automation in modern farming.

The AGRARIAN architecture leverages a diverse set of AI-driven technologies, IoT connectivity, and hybrid networking to transform modern agricultural practices. The table below highlights how different components of AGRARIAN align with key advancements in smart agriculture, mapping each technology to its impact on various domains such as precision irrigation, crop protection, livestock monitoring, and sustainable resource management. By associating AGRARIAN's sensor, network, data processing, and application layers with emerging decision support systems (DSS), AI models, and satellite-based remote sensing, this comparison demonstrates how AGRARIAN enhances efficiency, sustainability, and productivity across the agricultural sector.

Table 1 illustrates AGRARIAN's role in improving precision farming by integrating IoT and 5G for irrigation, AI-based disease detection, and satellite-powered monitoring. Through real-time sensor data collection, AI-powered decision-making, and seamless connectivity, AGRARIAN enhances resource management, reduces operational costs, and promotes environmental sustainability. Key findings indicate that edge AI and federated learning enable more localized and responsive agricultural intelligence, reducing reliance on centralized cloud computing while improving latency-sensitive applications like livestock health monitoring and irrigation control. By combining AI-enhanced DSS, machine learning-driven crop management, and satellite-based remote sensing, AGRARIAN provides a scalable, modular, and resilient digital agriculture platform that supports data-driven farming, climate adaptation, and food security initiatives.

Table 1. AGRARIAN related works table and how they are mapped to AGRARIAN layers.

AGRARIAN Component	Author, Year, Ref. No.	How AGRARIAN Benefits the Field	Mapped AGRARIAN Layer(s)	Benefit to Agriculture
IoT and 5G for Smart Irrigation	Oppong, R.A. (2025) [9]	Enhances precision irrigation by leveraging real-time sensor data.	Sensor Layer, Network Layer	Enhances irrigation efficiency, prevents overwatering, and improves water conservation.

Decision Support Systems (DSS) for Agrarian Policy	Vasylishyn, S. (2025) [10]	Provides AI-driven policy recommendations based on real-time agricultural data.	Application Layer, Data Processing Layer	Optimizes agricultural resource allocation, policy effectiveness, and economic sustainability.
AI-Based Crop Protection and DSS	Jensen, A. et al. (2025) [11]	Enables early disease detection and pest management through AI-powered analytics.	Data Processing Layer, Sensor Layer	Reduces pesticide use, increases farm productivity, and enhances sustainability.
CubeSats for Agricultural Monitoring	Calka, B.; Szostak, M. (2025) [12]	Offers high-resolution environmental monitoring for precision farming.	Sensor Layer, Network Layer	Provides real-time insights into soil health, crop growth, and environmental conditions.
Smart Agriculture and DSS for Water Resource Management	Firoozzare, A. et al. (2025) [13]	Improves sustainable water resource management using AI-driven climate data.	Application Layer, Data Processing Layer	Ensures sustainable water allocation, mitigates drought impacts, and supports climate resilience.
AI for Precision Livestock Farming	Distante, D. et al. (2025) [14]	Enhances livestock welfare via real-time biometric monitoring and disease detection.	Sensor Layer, Data Processing Layer	Reduces livestock mortality, increases efficiency, and improves farm profitability.
Sustainable Agricultural Planning using DSS	Kaynak, T.; Gümüş, M.G. (2025) [15]	Supports energy-efficient agriculture through AI-driven biogas plant planning.	Application Layer, Network Layer	Supports renewable energy integration and reduces the carbon footprint in agriculture.
Circular Bioeconomy and DSS in Agriculture	Nguyen, T.H. et al. (2025) [16]	Facilitates circular agriculture by optimizing waste recycling.	Application Layer, Data Processing Layer	Promotes waste reduction, circular economy strategies, and resource-efficient food production.
Digital Agriculture and AI Decision Systems	De, S.; Sanyal, D.K.; Mukherjee, I. (2025) [17]	Improves real-time farm management with AI-enhanced automation tools.	Application Layer, Data Processing Layer	Enhances farm decision-making with AI-driven insights and real-time analytics.
Digital Technologies for Sustainable Agriculture	Krachunova, T. et al. (2025) [18]	Enables sustainable farming through AI-integrated remote sensing and DSS tools.	Application Layer, Sensor Layer, Network Layer	Encourages climate-smart farming through AI, IoT, and sustainable land management practices.

4. Preliminary Validation of AGRARIAN over 5G Network Slicing for Data Processing and Sensor Layers

To validate the AGRARIAN architecture in terms of its integration with modern communication technologies, we conducted a series of experiments focusing on 5G network slicing and its implications on energy consumption and latency performance across system layers. These trials were designed to explore how eMBB (enhanced Mobile Broadband) slices align with AGRARIAN's Data Processing Layer, while uRLLC (ultra-Reliable Low Latency Communication) slices support the responsiveness required by the Sensor Layer. Experiments were executed on an experimental 5G system that was deployed in Standalone Mode (SA) using Amarisoft 5GC with Huawei P40 Pro UEs and OpenStack-based virtualized services running on a Dell R730xd. The slicing mechanism leveraged RAN numerology manipulation to enforce low-latency configurations via tuning of srPeriod and slot duration.

In the context of 5G network slicing, particularly at the RAN (Radio Access Network) level, srPeriod and slot are two key parameters that directly influence latency and scheduling responsiveness. The srPeriod (Scheduling Request Period) defines how frequently a user equipment (UE) can request uplink transmission resources, with lower values enabling faster response times, Table 2 provides a representative analysis of different configurations and corresponding latency metrics. The slot parameter represents the transmission duration within a time frame, affecting how quickly data can be scheduled and processed. Reducing both parameters leads to lower end-to-end latency, a critical factor for uRLLC (ultra-Reliable Low Latency Communication) performance in applications such as real-time sensor feedback and UAV coordination in smart agriculture. These parameters were varied across several configurations to examine their impact on latency and energy consumption under different slicing conditions.

Table 2. 5G network slicing configuration information and corresponding expected latency.

Configuration	srPeriod	Slot Duration	Expected Latency
Config 1 (Min Latency)	1	2.5	~10 ms
Config 2	1	5.0	~15–18 ms
Config 3	10	2.5	~20–25 ms
Config 4	10	5.0	~30 ms
Config 5	40	2.5	~35 ms
Config 6 (Max Latency)	40	5.0	~40 ms

The first set of experiments evaluated energy consumption under varying eMBB slice bitrates (100 to 300 Mbps) and latency configurations (10 ms and 40 ms). Results (Figure 6) revealed that smaller packet sizes significantly increase energy usage due to higher transmission frequency, and lower latency configurations consistently consume more energy, confirming a trade-off between latency and energy performance at the data processing level. To evaluate uRLLC slicing for the sensor layer, latency measurements were collected under diverse configurations. With an eMBB slice allocated for backhaul, multiple uRLLC slices were imposed (srPeriod = {1, 10, 40}, slot = {2.5, 5}). As illustrated in Figures 6 and 7, these settings significantly affected system latency, with the best result (~12 ms) observed under the most aggressive uRLLC configuration (sr = 1, slot = 2.5). These findings support AGRARIAN's capacity to provide low-latency edge responsiveness for sensor-triggered alerts and UAV communications.

To understand the impact of 5G slicing on energy efficiency in AGRARIAN's Data Processing Layer, we analyzed the energy consumption of downlink transmissions across different latency configurations and bitrate levels. These configurations, defined by the slicing parameters srPeriod and slot, were mapped to typical eMBB profiles. Figure 6 presents a 3D surface plot illustrating energy usage (in mA) as a function of both bitrate and latency configuration, offering a visual overview of the trade-offs involved.

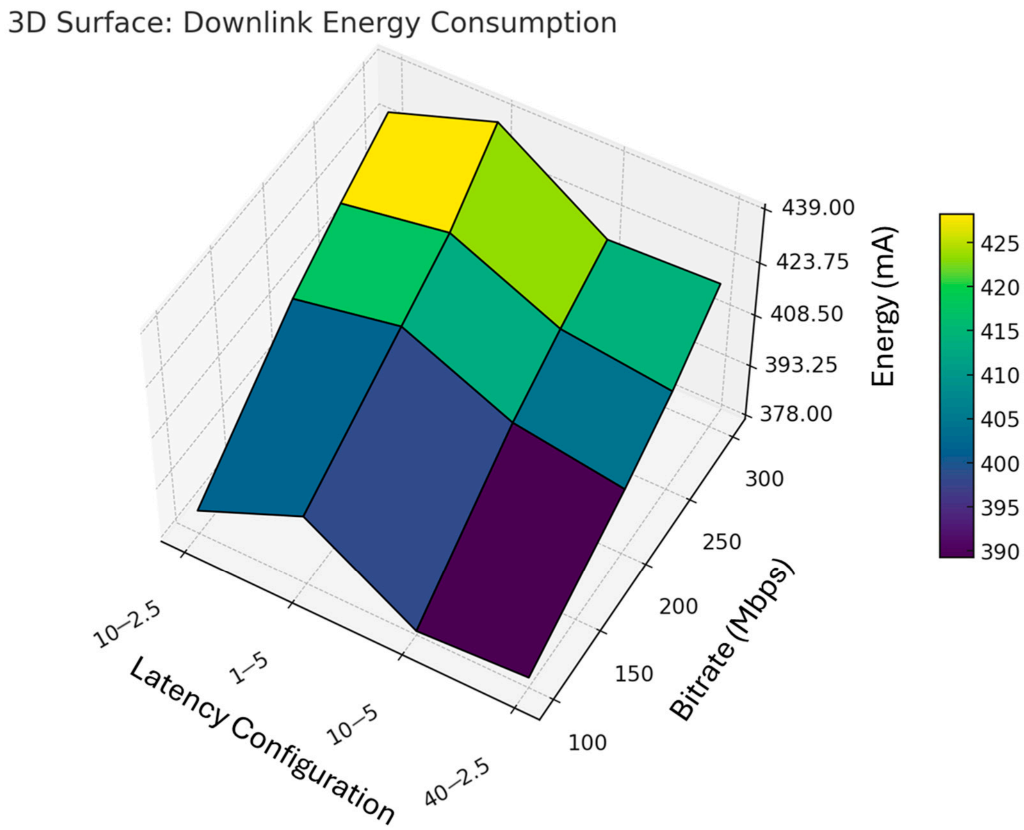

Figure 6. A 3D Surface Plot of Downlink Energy Consumption across Bitrate and Latency Configurations.

From the surface plot, it becomes evident that energy consumption increases with both higher bitrates and more aggressive low-latency configurations. This validates the architectural decision to employ edge computing in AGRARIAN's data processing layer, where compute-intensive tasks can be selectively handled based on energy budgets. The visualization confirms that while high throughput improves data processing responsiveness, it should be balanced against energy constraints—especially for deployments in energy-limited environments such as remote or sensor-heavy agricultural fields.

Complementing the downlink analysis, Figure 7 visualizes uplink energy consumption, which is particularly relevant to the Sensor Layer in AGRARIAN. This layer frequently transmits real-time data from IoT sensors and UAVs back to the system. The 3D surface plot represents energy consumption across the same set of latency configurations and bitrates, this time focusing on the energy demand of uplink transmissions under different uRLLC slice conditions.

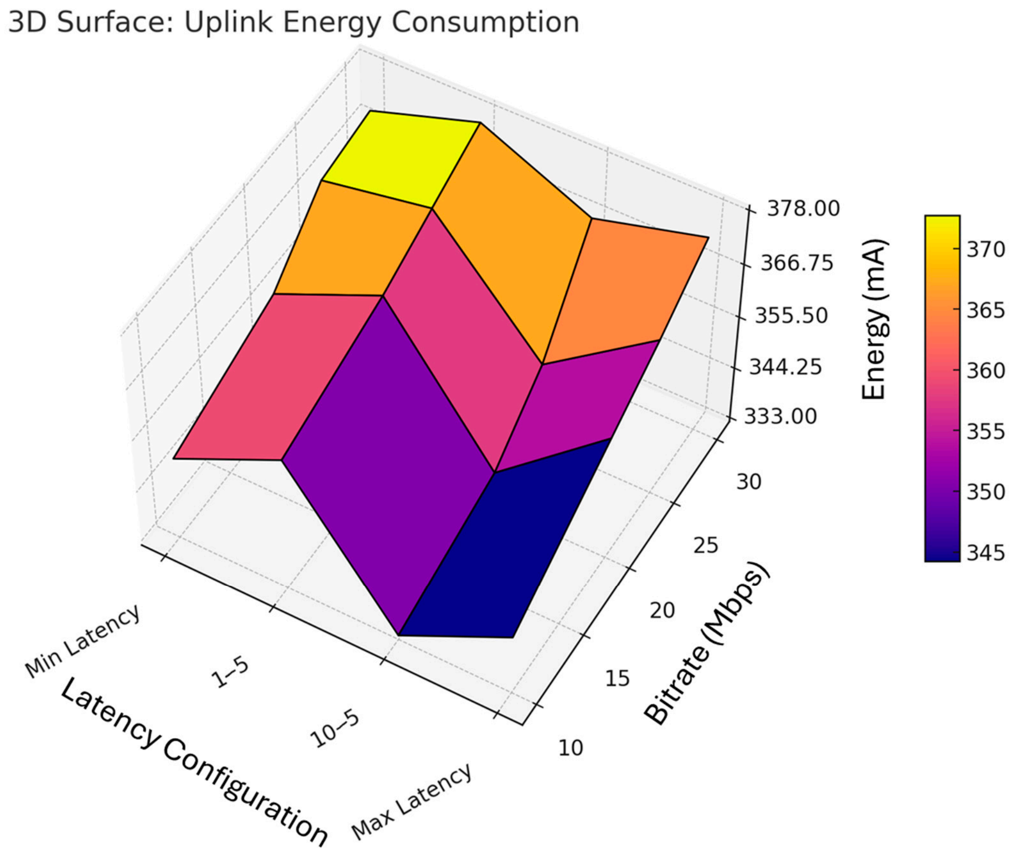

Figure 7. A 3D Surface Plot of Uplink Energy Consumption across Bitrate and Latency Configurations.

The plot reveals a similar trend to the downlink case—energy usage escalates under low-latency configurations and higher data rates, reinforcing the known latency-energy trade-off. However, because the sensor layer often operates with small, frequent packets rather than continuous streams, the relative energy cost becomes a critical design parameter. These findings support AGRARIAN's conservative approach to using uRLLC slices only where real-time sensing is essential while deferring less critical transmissions to energy-optimized configurations. This balance allows for both performance and energy efficiency in field deployments.

5. Conclusions

The AGRARIAN architecture offers a modular and intelligent framework for modern agriculture, combining IoT sensors, UAVs, satellite connectivity, edge computing, and AI-based analytics to enhance precision farming and sustainability. By decentralizing data processing and enabling real-time insights through edge AI, AGRARIAN supports efficient, scalable, and resilient agricultural operations. Its layered design ensures adaptability across various farming environments and levels of digital maturity.

In contrast to conventional cloud-centric systems, AGRARIAN supports hybrid deployment models that reduce connectivity constraints and promote real-time decision-making where it is contextually valuable. Pilot implementations demonstrate its relevance for applications such as irrigation control, crop disease alerts, and livestock monitoring. Future work will focus on expanding AGRARIAN's integration with agricultural machinery, enhancing interoperability, and validating its performance across broader agro-ecological zones.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
DSS	Decision Support System
IoT	Internet of Things
UAV	Unmanned Aerial Vehicle
LEO	Low Earth Orbit
GEO	Geostationary Earth Orbit
SAR	Synthetic Aperture Radar
5G NTN	5G Non-Terrestrial Network
RINA	Recursive InterNetwork Architecture
NETCONF	Network Configuration Protocol
YANG	Yet Another Next Generation
DTN	Delay-Tolerant Networking
MCDA	Multi-Criteria Decision Analysis
GIS	Geographic Information System
EO	Earth Observation

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