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Electromechanical control architecture for automated tillage and irrigation systems

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ABSTRACT

Efficient agricultural automation requires an electromechanical architecture capable of integrating sensing, actuation, communication, and interfaces for autonomous machinery while keeping performance claims traceable to their evidence. This study addressed this problem using an analytical system-design approach and a comparative engineering analysis of literature-derived quantitative benchmarks. Unlike studies treating irrigation, robotic interfaces, and connectivity separately, the proposed framework integrates these functions while separating design features from literature-derived evidence. Quantitative values were treated as literature-derived benchmarks rather than original field measurements. Reported automation technologies indicated water-saving ranges of 20%–50%, while precision dosing benchmarks reduced fertiliser consumption from 45–50 to 28–32 L ha−1 cycle−1 and water loss from 10%–12% to ≤2%. The analysis indicated that local sensor-based closed-loop control provided the principal mechanism for resource savings, whereas remote connectivity primarily supported supervision and data exchange. No artificial-intelligence or machine-learning controller was implemented. The proposed architecture therefore established a reproducible automation framework and a pathway towards future autonomous robotic validation.

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1. INTRODUCTION

Automation is increasingly central to precision agriculture because water, energy, fertiliser, and machinery must be managed in response to spatially and temporally variable field conditions. Precision-agriculture systems combine sensing, positioning, data processing, and automated actuation to improve resource utilisation [1]. Within this broader context, smart irrigation has progressed from fixed scheduling towards cyber-physical control, in which soil and environmental data inform water-delivery decisions [2]. IoT architectures extend this capability through distributed sensing, connectivity, and remote supervision [3], [4], while improving water-use efficiency remains especially important in water-constrained agricultural environments [5].

The principal engineering problem is that sensing, decision making, actuation, communication, safety, and mobile-machine operation must function as a coherent system rather than as independent components. Electromechanical control provides the physical link between measured field conditions and

agricultural operations: digital machinery control can improve the repeatability of operating parameters and reduce reliance on manual adjustment [6], and sensor-controlled drip irrigation can reduce unnecessary water delivery [7]. Nevertheless, system performance depends not merely on installing sensors or actuators, but on how measurements are validated, translated into local control decisions, communicated, and executed under safe operating constraints.

The state of the art reflects a growing convergence of IoT-enabled control, cyber-physical agriculture, and field robotics. Contemporary field-management robots integrate electric drives, multi-sensor perception, autonomous navigation, and implement control on a single mobile platform [8]. Distributed sensor modules and controller area network communication have been experimentally applied to autonomous navigation and collision avoidance [9], while vision-based crop-row navigation has been evaluated under variable crop growth, weeds, discontinuities, shadows, and illumination [10]. Field trials of autonomous electric agricultural robots further indicate that navigation accuracy, implement interaction, energy consumption, and working capacity should be assessed as interdependent system properties [11]. Together, these studies establish important capabilities, but they generally evaluate smart-irrigation control, sensing, robotic navigation, implement operation, or energy performance within distinct platforms and experimental settings.

A gap therefore remains between isolated technological demonstrations and a unified, traceable electromechanical architecture for coordinated tillage and irrigation. Prior smart-irrigation systems primarily establish sensor-to-valve or sensor-to-pump control, whereas robotic studies primarily validate navigation, mobility, collision avoidance, or implement performance. Their numerical results arise from different crops, fields, hardware configurations, operating periods, baselines, and control strategies and thus cannot be treated as directly comparable performance measurements of one integrated system. The analysed literature does not provide a common architecture that connects process sensing and actuation for tillage and irrigation with local decision making, communication hierarchy, fail-safe operation, and a defined interface for future autonomous agricultural robots.

This study addresses that gap by proposing a modular electromechanical control architecture that integrates sensing, signal validation, deterministic local control, irrigation and tillage actuation, communication, safety logic, and robot interfacing within one technical framework. Its novelty lies not in claiming that each component is individually new, but in specifying their functional integration while rigorously separating the proposed design contribution from quantitative benchmarks derived from heterogeneous literature. This separation is treated as a methodological innovation because it preserves evidence traceability, prevents literature-reported values from being misrepresented as results of the proposed architecture, and defines which performance claims still require experimental verification. Accordingly, the study asks: how can such an architecture be specified as a technically coherent and evidence-traceable system? The objectives are to i) define its modular hardware, communication, and control structure; ii) compare principal sensing, irrigation, dosing, communication, and power-supply alternatives using consistently identified indicators; and iii) specify its interface with autonomous agricultural robotic platforms.

The significance of the proposed approach is that it establishes a reproducible pathway from architecture design to future autonomous robotic validation. By distinguishing design specifications from literature-derived benchmarks, quantitative performance ranges, technical characteristics, and cost ranges obtained from previously published studies rather than measuredments of the proposed system, the study provides a transparent basis for selecting components, defining testable interfaces, and establishing validation requirements before construction of an integrated prototype. Future studies can therefore implement the architecture and evaluate it through documented sensor calibration, repeated field trials, predefined safety and communication tests, robot–implement interaction measures, and quantitative assessment of water use, energy demand, operating capacity, and control accuracy. This staged pathway supports cumulative comparison across subsequent prototypes while ensuring that claims about autonomous performance are based on directly generated evidence.

2. METHOD

The analytical design work was conducted at the Educational and Practical Centre of Mykolaiv National Agrarian University in 2023–2024. The study was structured as an electromechanical system-design and comparative engineering analysis. Two categories of evidence were kept separate throughout the study. The first category comprised the proposed architecture developed in this study, including the functional hardware structure, local control workflow, communication hierarchy, safety logic, and interface with autonomous agricultural machinery. These elements represent the design contribution of the study. The second category comprised quantitative values reported in previous studies and synthesised for the

comparative engineering analysis. These numerical values were treated as literature-derived engineering benchmarks and not as measurements generated by field implementation of the complete proposed architecture. The same distinction was applied to comparisons with recent smart-irrigation and agricultural-robotic systems. The study was not treated as a systematic review or meta-analysis, and no pooled effect estimate was calculated because the compared publications differed in hardware, crops, operating conditions, performance definitions, and experimental designs.

No replicate-level field dataset from a complete integrated prototype was used as evidence for the quantitative performance comparisons in the present study. Therefore, field dimensions, crop type, soil characteristics, experimental operating duration, irrigation schedule, experimental sampling frequency, and sensor-calibration records are not presented as measured parameters of the proposed architecture. These variables are instead identified as mandatory parameters for subsequent prototype validation. Accordingly, the literature-derived benchmarks do not constitute evidence from a single integrated field experiment.

The comparison focused on performance indicators that could be interpreted without treating heterogeneous studies as a pooled experiment. The indicators included water saving relative to a stated baseline, sensor accuracy, measurement depth, fertiliser consumption, dosing deviation, water loss, yield where reported in the cited studies, maintenance requirement, power range, installation cost, payback period, navigation performance, robotic working capacity, and energy consumption. Where a water-saving percentage S_w was reported relative to baseline water consumption Q_b and automated-system consumption Q_a, it was interpreted according to:

$$S_w = \frac{Q_b - Q_a}{Q_b} \times 100\%$$

Comparisons were interpreted as descriptive engineering benchmarks rather than pooled experimental effect estimates. Where the comparative sources reported ranges or other measures of variability, those values were retained as reported. Consequently, the numerical benchmarks describe performance associated with the cited technologies and cannot be interpreted as statistically validated performance of the proposed architecture. Future field validation should use repeated experiments, predetermined evaluation metrics, calibration records, measures of variability, and appropriate confidence intervals or significance tests.

The proposed architecture has moderate computational complexity because its core functions, sensor validation, three-sample median filtering, threshold comparison, fault detection, actuator control, and event logging, require limited processing and memory and can be implemented on a standard embedded controller. Integration is feasible through widely used interfaces, including analogue and digital inputs, RS-485/Modbus for stationary field devices, CAN for robot-integrated modules, and Ethernet or MQTT-based gateways for supervisory communication. Its modular design permits sensors, actuators, and robotic platforms to be added incrementally without modifying the deterministic local safety logic, although practical deployment still requires interface compatibility testing, timing verification, power-budget assessment, and field validation.

3. RESULTS AND DISCUSSION

The proposed system was designed as a modular hierarchical architecture in which time-critical irrigation and implement-control decisions are executed locally, while remote communication is used for supervision, logging, and higher-level coordination. This separation prevents basic actuator operation from depending on continuous Internet availability. The architecture contains field sensors, signal acquisition and validation, a local controller, actuator interfaces, a communication gateway, a safety layer, and an interface to an autonomous agricultural robot or mobile field platform.

Soil-moisture sensors provide the principal feedback variable for irrigation demand. Temperature measurements provide environmental context, whereas pressure measurements are used to detect insufficient pressure, excessive pressure, leakage-related deviations, or unstable hydraulic operation. pH sensing can support fertigation supervision where nutrient dosing is included. Sensors are connected to the local controller through analogue, digital, or industrial fieldbus interfaces according to sensor type.

The controller specification is functional rather than manufacturer-specific because the present study defines a system architecture rather than a validated commercial controller configuration, as seen in Table 1. The controller should provide multichannel analogue and digital inputs, digital or relay outputs for actuator switching, variable-speed-drive command capability where proportional pump control is required, watchdog protection, non-volatile event logging, and wired communication interfaces. RS-485/Modbus communication is proposed for stationary distributed field devices, whereas CAN communication is proposed for mobile agricultural machinery and robot-integrated modules. Ethernet can connect higher-level controllers and

gateways. Wi-Fi or cellular communication using an application-layer protocol such as MQTT can provide supervisory IoT connectivity. Wireless communication is not included in the safety-critical local feedback loop.

Table 1. Functional specification of the proposed electromechanical control architecture

Subsystem	Proposed components or functions	Interface	Main function
Environmental sensing	Soil-moisture and temperature sensors	Analogue/digital or fieldbus	Determine irrigation demand and environmental state
Hydraulic sensing	Pressure sensor	Analogue or industrial transmitter	Verify hydraulic conditions and detect abnormal states
Fertigation sensing	pH sensor	Analogue/digital	Supervise nutrient-solution condition
Local controller	Embedded or PLC-class controller, analogue/digital I/O, watchdog, local storage	RS-485, CAN, Ethernet	Execute deterministic local control and safety logic
Actuator interface	Relays, motor drivers, variable-speed drives	Digital, analogue command, or fieldbus	Control valves, pumps, and dosing devices
Communication gateway	Wired and wireless gateway	RS-485/Modbus, CAN, Ethernet, Wi-Fi/cellular, MQTT	Connect field equipment, supervisory platform, and robot controller
Software framework	Validation, median filtering, state machine, logging, alarms	Local controller software	Convert sensor information into validated commands
Robot interface	Navigation/status and implement-control gateway	CAN or Ethernet	Coordinate process actuation with autonomous robot state
Safety layer	Watchdog, timeout, plausibility checking, safe-off state, manual override	Local	Prevent uncontrolled actuation during faults

The architecture shown in Figure 1 provides a closed information path from sensing to local decision making and actuation. A separate communication branch provides supervision and higher-level coordination, while the robot interface enables position, operating state, and task information to be exchanged with an autonomous agricultural platform.

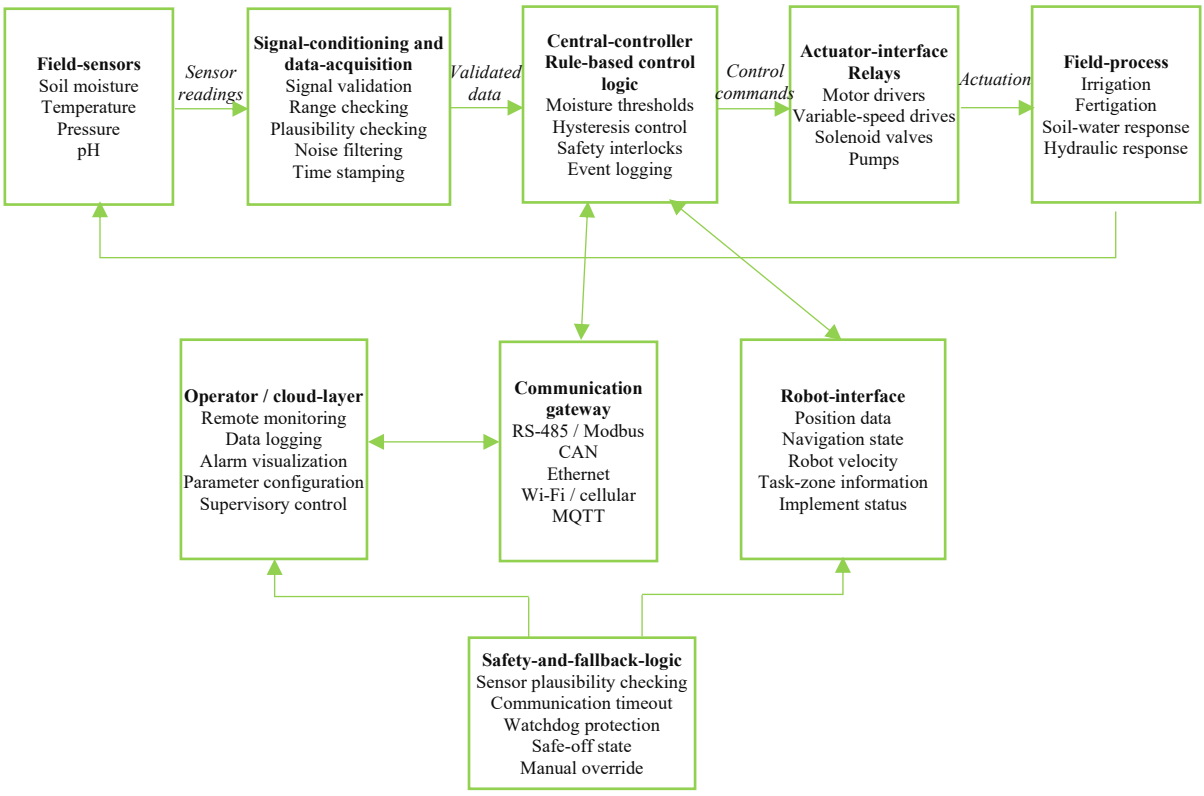

Figure 1. Proposed electromechanical control architecture for automated tillage and irrigation systems

The proposed control workflow consists of acquisition, validation, filtering, decision, actuation, and logging stages. Sensor data are sampled, time-stamped, and validated through range and plausibility checks before use by the controller. Missing values, communication failures, out-of-range measurements, and physically inconsistent readings are classified as faults. Valid signals pass through a three-sample median filter to reduce isolated noise before comparison with configurable control thresholds. For irrigation control, soil moisture is the primary feedback variable. Two configurable moisture thresholds form a hysteresis band: irrigation starts when validated moisture falls below the lower threshold and safety conditions are satisfied, and stops when the upper threshold is reached or when faults or safety interlocks occur. This approach prevents unnecessary actuator switching. Pressure monitoring provides hydraulic fault detection, while pH and dosing status are monitored during fertigation. Control states and faults are stored locally, while supervisory data may be transmitted remotely without affecting the local control loop.

The software framework applies deterministic rule-based control. No artificial intelligence, machine learning, deep learning, reinforcement learning, or adaptive-learning algorithms were implemented or experimentally validated in this study. These approaches are considered future extensions requiring integrated prototypes and sufficient field datasets. For autonomous robotic integration, the electromechanical module functions as an implement-level controller: the robot provides navigation, position, velocity, and task information, while the controller returns sensor states, actuator status, alarms, and task-completion data through CAN, Ethernet, or suitable middleware interfaces.

This separation ensures safe autonomous operation: navigation determines task execution conditions, whereas the local controller determines whether irrigation, dosing, or other actuators can operate safely. Loss of higher-level communication should not compromise actuator safety, as the local controller maintains independent safe-state functionality. The first research objective addressed the relationship between automation functionality and water-use performance. Sidhu *et al.* [12] investigated drip irrigation automation and water-use efficiency in cereal production systems, providing relevant benchmarks for the irrigation technologies analysed in this study. Literature-based quantitative benchmarks are presented in Table 2.

Table 2. Literature-derived water-saving benchmarks for irrigation automation technologies [13]

Technology	Control function	Reported water saving (%)
Solenoid valves (Rain Bird 100 Series)	Controller-based opening and closing of water supply	20–30
Motorised pumps (Grundfos CR 15-4)	Automatic water-supply control according to pressure and moisture	30–40
IoT systems (Decagon Devices)	Remote monitoring, control, and data analysis	40–50

Note: The reported baseline was conventional irrigation consumption of approximately 50-60 L ha-1 cycle−1.

The principal engineering mechanism is increasingly selective water delivery. Valve automation allows discrete control of water supply, whereas moisture- and pressure-dependent pump control adds direct process feedback. IoT connectivity adds supervision, logging, remote parameter adjustment, and data access, but connectivity itself does not physically reduce water consumption. Resource savings arise when validated measurements are used to suppress unnecessary or excessive irrigation. This interpretation supports the architecture, in which the local feedback loop remains responsible for time-critical decisions while the IoT layer performs supervisory functions. A recent experimentally evaluated smart-irrigation system based on real-time soil-moisture feedback reported approximately 25% to 35% lower water consumption than fixed-schedule irrigation, demonstrating the practical relevance of sensor-informed water delivery while also showing that the magnitude of savings depends on system and field conditions [13].

The second research objective concerned the sensing and dosing components required for feedback-based control. Soil-moisture measurement quality is particularly important because measurement uncertainty directly affects the reliability of irrigation decisions. The literature-derived sensor characteristics are presented in Table 3.

Table 3. Literature-derived comparison of soil-moisture sensors

Sensor type	Sensitivity (1–10)	Measurement depth (cm)	Accuracy (%)	Connection method	Price (USD)
Capacitive (Decagon Devices)	8	5–50	±3–5	Analogue/digital	20–100
Resistive (Soil Moisture Equipment Corp.)	5	5–10	±10–15	Analogue	5–20
Time-domain reflectometry (Spectrum Technologies)	10	10–100	±1–3	Digital	100–500

Note: The values are literature-derived engineering benchmarks reported in [14] and are not measurements obtained from the proposed architecture.

The comparison demonstrates an engineering trade-off between acquisition cost, measurement range, and accuracy. Resistive sensing provides the lowest reported acquisition cost but also the lowest reported accuracy and the shallowest measurement range, whereas time-domain reflectometry provides greater reported accuracy and measurement depth at substantially higher cost. Capacitive sensing occupies an intermediate position. Sensor selection for an automated or robotic system should therefore consider measurement uncertainty, installation depth, calibration stability, interface compatibility, and replacement requirements rather than purchase price alone [15], [16].

Table 4. Literature-derived comparison of standard and sensor-controlled dosing [17]

Parameter	Standard dosing (Grundfos Dosing)	Precision dosing (Rain Bird ESP-LXME)
Fertiliser consumption (L ha−1 cycle−1)	45–50	28–32
Deviation from specified dose (%)	±15	±3
Water loss due to overdose (%)	10–12	≤2
Yield (t ha−1)	8.2	9.1
Environmental-impact assessment	Average	Low
System maintenance time (h week−1)	5	2.5

The engineering significance of this comparison lies in the simultaneous change in resource use and control accuracy. A lower deviation from the specified dose indicates that the actuator-controller combination more closely reproduces the target application rate. Reduced dosing error consequently decreases the likelihood of over-application and provides a direct mechanism for lowering fertiliser consumption and associated water loss. Precision-irrigation studies similarly indicate that matching water and nutrient application to measured field conditions can reduce resource losses [18], [19]. The third research objective concerned the communication and supporting energy infrastructure required for automated and potentially autonomous operation. Remote connectivity is most useful when it complements rather than replaces deterministic local control. IoT-based platforms can provide remote access to irrigation status, historical data, alarms, and operating parameters [20], whereas the local controller should preserve safe basic operation during loss of external connectivity.

Communication reliability is therefore treated as an architectural requirement. Network latency, packet loss, unstable cellular coverage, or gateway failure may interrupt supervision but should not directly remove local safety functions. This hierarchy is particularly important when the control unit is integrated into an autonomous agricultural platform.

Table 5. Literature-derived technical and economic ranges of alternative energy options [21]

Energy source	Reported power range (W)	Installation cost (USD)	Payback period (years)	Reported environmental characteristic
Solar panels	100–5,000	500–10,000	3–7	Low CO_2 emissions
Wind turbines	500–10,000	2,000–20,000	5–10	Minimal operational impact
Rechargeable batteries	100–5,000	300–5,000	2–5	No direct operational emissions

Note: The power range reported for rechargeable batteries should not be interpreted as an equivalent measure of battery energy-storage capacity.

A scenario-based sensitivity analysis was conducted to examine the robustness of the proposed architecture under uncertainty in sensor accuracy, communication reliability, and energy availability. Sensor measurement error was varied from ±1% to ±15%, consistent with the literature-derived ranges in Table 3, while communication reliability was assessed under packet-delivery levels of 99%, 95%, and 90%. Energy alternatives in Table 5 were evaluated at 100%, 75%, and 50% of their nominal available power to represent normal operation, moderate derating, and adverse field conditions. These scenarios are analytical assumptions rather than experimentally measured performance values.

The analysis indicated that sensor accuracy had the greatest direct influence on irrigation decisions because increasing measurement error raised the likelihood of premature or delayed threshold activation. Reduced communication reliability primarily affected remote monitoring and data exchange, while deterministic local control and safety functions remained operational because they did not depend on continuous connectivity. Energy-source derating had limited consequences for sensors and control electronics but could restrict pump, propulsion, and implement operation; therefore, rechargeable storage or a hybrid solar–battery configuration provides greater operational resilience than reliance on a single intermittent source.

Renewable-energy technologies can improve the autonomy of field installations where grid access is limited [21]–[23]. However, an autonomous agricultural platform requires a complete power budget rather than only the nominal output of the energy source. Sensors and local control electronics represent a different load category from pumps, propulsion motors, and high-power agricultural implements. Consequently, the energy requirements of stationary irrigation control and mobile robotic operation should be evaluated separately during prototype validation. To position the proposed architecture within current agricultural automation and robotics, Table 6 compares representative recent systems using the principal quantitative or experimentally defined performance indicator reported by each study. The indicators are not pooled because the systems perform different tasks and were evaluated under different operating conditions.

Table 6. Comparison with recent agricultural robotic and smart-irrigation systems

Study/system	Application and validation context	Principal reported performance
Boukri *et al.* [13]	Soil-moisture-based IoT irrigation; field evaluation	25%–35% lower water use than fixed-schedule irrigation
Cui *et al.* [8]	Multifunctional autonomous field-management robot	44.79 mm average and 79.40 mm maximum path-tracking error in straight-operation sections
de Silva *et al.* [10]	Vision-based crop-row navigation	Robust guidance was demonstrated with initial orientation errors up to 20° under 11 categories of field variation
Sara *et al.* [11]	Autonomous electric agricultural robot for tillage and weeding	0.71–0.77 m s−1 sustained field speed, approximately 1.43 kWh h−1 energy consumption, 0.29 ha h−1 working capacity, and 40% weed removal in a single pass
Present study	Proposed electromechanical tillage/irrigation control architecture	Architecture and integration contribution; no original integrated field-performance value claimed

The comparison demonstrates why performance claims must remain task-specific. A millimetre-level path-tracking error is meaningful for robotic navigation but does not quantify irrigation efficiency, whereas water saving is meaningful for process control but does not demonstrate autonomous mobility. Energy consumption characterises the operating burden of a mobile robot but does not independently establish sensor or dosing accuracy [24]–[26]. The contribution of the present study is therefore not a claim that one literature-derived percentage represents the performance of the complete integrated system. Instead, the proposed architecture defines how sensing, actuation, communication, safety, and robotic interfaces can be combined and which variables must be measured when the integrated system is subsequently subjected to field validation. Recent agricultural-robot studies further support the architectural emphasis on modular local sensing and communication. Distributed sensor modules with CAN communication, local processing, Ethernet connectivity, and robot operating system integration have been experimentally validated for agricultural mobile-robot navigation and collision avoidance [9].

The key finding was that a technically coherent agricultural automation architecture requires deterministic local sensing and actuation to remain independent of higher-level connectivity, while supervisory communication and robotic interfaces provide coordination rather than replacing the local control loop. The comparative evidence further indicated that the principal resource-saving mechanism across the analysed irrigation technologies was sensor-informed control of water and nutrient delivery rather than connectivity alone. The significance of the proposed architecture lies in connecting process-level agricultural automation with the requirements of autonomous field machinery [27]. By separating deterministic local control from supervisory communication, the architecture can support irrigation and dosing functions without making safety-critical actuator operation dependent on network availability. The same modular structure can serve as an implement-control layer for future agricultural robots, in which navigation and mission planning operate at a higher level while field-process decisions remain locally validated.

The technical validity of the proposed architecture is supported by its alignment with established requirements for agricultural automation and robotics. Its use of modular electronic control units and CAN-based communication is consistent with the interoperability principles of ISO 11783 for communication between agricultural machinery components, while its separation of safety-critical local control from supervisory connectivity corresponds to the risk-reduction and safety-related control principles of ISO 25119. Sensor validation, watchdog protection, fault logging, communication-timeout detection, actuator interlocks, and transition to a predefined safe state also address the functional-safety expectations applicable to electronically controlled agricultural machinery.

For integration with autonomous field robots, the architecture additionally reflects ISO 18497 requirements concerning hazard detection, controlled operation, operator notification, and safe responses to faults or loss of communication. Nevertheless, this comparison demonstrates requirements-level compatibility rather than formal compliance or certification. Technical conformity must be confirmed through prototype-level risk assessment, communication and electromagnetic-compatibility testing, verification of safety functions and stopping behaviour, environmental durability tests, and documented validation under representative field conditions.

For autonomous agricultural robotics, the proposed architecture provides an implement-level control layer beneath navigation and mission planning. Existing robots confirm the importance of modular sensing, local processing, fieldbus communication, navigation, and robustness under variable field conditions [8]–[11]. The controller could integrate local process feedback with robot position, operating state, and task-zone information. Artificial intelligence and machine learning could later support sensor fusion, water-demand prediction, crop-state recognition, and adaptive set-point selection [28], [29], while variable-rate actuation, unmanned-farm control, precision-farming integration, and electromechanical powertrains offer further development directions [30]–[33]. However, these functions should follow validation of the deterministic architecture through repeated field experiments.

Cui *et al.* [8] showed that agricultural robots require coordination among navigation, sensing, electromechanical drive, and implement control, reporting average and maximum path-tracking errors of 44.79 and 79.40 mm, respectively. The present architecture complements this approach by defining an implement-level layer for sensor validation, local decisions, hydraulic actuation, and safety supervision. When integrated with such a navigation platform, the robot controller would determine location and task state, while the local controller would verify whether irrigation or fertigation could proceed safely. Shamshiri *et al.* [9] demonstrated the value of distributed sensor nodes and CAN communication in agricultural robots. Similarly, the proposed architecture uses CAN for robot-integrated modules and RS-485/Modbus for stationary devices, extending modular communication to soil-moisture, pressure, and pH sensing, actuator control, fault handling, and safe-off operation.

The crop-row navigation system of de Silva *et al.* [10] maintained robustness under variations in illumination, weeds, crop discontinuities, and robot orientation. The present study addresses complementary implement-level risks, including sensor faults, communication timeouts, hydraulic abnormalities, and environmental variability. A complete autonomous platform therefore requires both robust navigation and reliable local actuation. Sara *et al.* [11] evaluated an electric agricultural robot under field conditions, reporting operating speeds of 0.71–0.77 m s^{-1}, energy consumption of approximately 1.43 kWh h^{-1}, a working capacity of 0.29 ha h^{-1}, and 40% weed removal per pass. These findings show that autonomous systems must be assessed through control accuracy, energy demand, field capacity, and task effectiveness. Unlike that experimentally validated robot, the present contribution remains architectural. Future validation should combine the proposed control metrics with navigation accuracy, energy consumption, field capacity, task completion, and communication reliability.

The proposed architecture can guide prototype development by providing a modular framework for selecting, integrating, and testing sensors, controllers, communication interfaces, actuators, safety functions, and energy sources in successive implementation stages. In real-world agricultural contexts, this structure allows developers to adapt the prototype to field size, soil and crop conditions, irrigation infrastructure, connectivity, and available power while prioritising local control of water and fertiliser application [34]. Its sensor-informed feedback, fault detection, event logging, and configurable operating thresholds can support more efficient use of water, nutrients, energy, labour, and maintenance resources; however, the resulting benefits should be verified through site-specific calibration, repeated field trials, and documented resource-consumption measurements.

For farmers, the proposed architecture offers a phased adoption pathway in which sensing, automated irrigation, communication, and robotic functions can be added according to operational needs and available budgets, reducing the financial risk of immediate full-scale deployment. Engineers can balance initial cost against measurement accuracy, energy demand, maintenance requirements, and component durability while using local control, fault detection, protected interfaces, and replaceable modules to improve reliability under harsh field conditions [35], [36]. Robotics developers can integrate the architecture as a modular implement-control layer through standard communication interfaces without redesigning navigation and mission-planning systems. Scalability can be achieved by extending the system from a single controller and several sensors to distributed field nodes and gateways, although larger deployments require network redundancy, synchronisation, power-budget assessment, calibration planning, and structured maintenance [37], [38].

Several limitations must be considered before practical deployment. First, the present study proposes an architecture and analyses literature-derived benchmarks but does not provide field validation of the complete integrated system. The reported numerical values therefore cannot be presented as experimental

performance of the proposed controller. Second, deployment cost increases with sensor accuracy, the number of monitored zones, communication infrastructure, actuator count, and redundancy requirements. Low-cost sensors can reduce initial investment but may increase calibration and replacement requirements, whereas higher-accuracy instrumentation can improve measurement reliability at a higher capital cost. Third, scalability creates communication and data-management challenges.

A small installation can connect several sensors directly to one controller, whereas a large farm may require distributed nodes, addressing, synchronisation, gateway redundancy, and fault localisation. Local control should therefore remain operational when remote communication is unavailable. Fourth, agricultural environments can accelerate sensor and connector degradation. Moisture, dust, temperature cycles, chemicals, mechanical vibration, and biological contamination may cause drift or failure. Calibration checks, plausibility diagnostics, replaceable sensor modules, protected connectors, and scheduled maintenance are therefore required for long-term operation. Fifth, communication reliability remains a constraint for remote or autonomous deployment. Packet loss, network latency, unstable wireless coverage, and gateway failure may interrupt supervisory communication. Safety-critical decisions should consequently remain within the local control layer. Sixth, robustness under different soils, crops, topographies, climates, irrigation technologies, and machinery configurations remains unverified. The descriptive cross-study values reported here cannot be freely extrapolated to all agricultural conditions.

4. CONCLUSION

This study proposed a modular electromechanical control architecture integrating environmental and hydraulic sensing, deterministic local decision making, actuator control, communication, fault handling, and an interface for autonomous agricultural machinery. Its principal scientific contribution was the explicit separation of the authors' system-level design from quantitative performance values derived from previous studies, thereby preventing literature-based benchmarks from being interpreted as original experimental results. The comparative analysis indicated that sensor-based local feedback is the principal mechanism through which automated irrigation and dosing can reduce unnecessary resource application, whereas IoT connectivity primarily extends supervision, logging, and higher-level coordination. The architecture also provides a technical basis for implement-level integration with autonomous agricultural robots by separating navigation and mission management from safety-critical local actuation.

Beyond its engineering application, the proposed architecture has educational value as a case study for agricultural automation, mechatronics, embedded control, and agricultural robotics courses. Its modular structure enables students to examine the complete sensing–validation–decision–actuation–communication pathway, compare alternative alternatives according to cost, accuracy, reliability, energy demand, and scalability, and design prototype subsystems without treating literature-derived benchmarks as experimental results. The architecture can therefore support laboratory exercises, simulation projects, system-integration assignments, risk assessments, and multidisciplinary capstone projects that connect control theory with practical agricultural resource management and autonomous machinery development.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, OS.

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