Enhancing Agricultural Audit Systems with IoT and Predictive Analytics: Deployment and Performance

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***Abstract*— This article proposes an extension of a geospatial-based agricultural audit platform by integrating Internet of Things technologies and predictive analytics. It builds on previous work to address field connectivity, scalability, and risk anticipation. The proposal outlines a modular architecture, identifies technical challenges and mitigation strategies, and presents use cases for different user profiles. Ethical, legal, and environmental implications of digitalisation are also discussed. This conceptual work supports future experimental validation and highlights the potential of digital transformation to enhance compliance with the Common Agricultural Policy and align with the European Green Deal priorities.**

Keywords—agricultural audit management, internet of things, predictive analytics, geospatial data integration.

I. Introduction

Digital management of agricultural audits is crucial for compliance with Common Agricultural Policy (CAP) standards, especially considering the growing complexity of compliance criteria, the geographical dispersion of farms and the need for strict resource management [1], [2], [3]. Previous work has seen the development of a technological platform that centralises agricultural audit processes by integrating geospatial data with management and visualisation tools, demonstrating operational gains in simulated environments [4], [5], [6].

However, the evolution of regulatory and operational requirements highlights the need for more intelligent and responsive systems. Emerging technologies such as the Internet of Things (IoT) are transforming the agricultural sector by enabling the continuous collection of soil, climate and crop data in real-time [7], [8], [9]. The authors [10] and [11] demonstrated that IoT sensors applied to agriculture improve resource efficiency and enable more precise interventions. Concurrently, Artificial Intelligence (AI) algorithms and predictive analytics have demonstrated significant potential in anticipating patterns of non-compliance, agricultural productivity, and operational failures, thereby enhancing the proactive nature of decision-making processes [12], [13].

However, the combined application of these technologies in agricultural auditing platforms, particularly within the CAP framework, remains in its early stages [14], [15]. The authors [16] and [17] argue that effective agricultural information systems require modular, interoperable and data-driven architectures, and the need for integrated, scalable platforms is widely recognised.

This article builds upon the foundations established in a previous study focused on the development of a geospatial platform for farm audit management. It extends that work by proposing an enhanced conceptual architecture that incorporates IoT integration, predictive analysis, and offline capabilities for field operations. The objective is to contribute to the development of a new generation of digital agricultural audit systems that are proactive, scalable and aligned with the principles of regulatory compliance and social responsibility.

Although this proposal is not accompanied by experimental validation or real-world metrics at this stage, it lays the foundation for future deployment and performance evaluation. The paper presents a conceptual roadmap, outlines the technical and ethical dimensions, and identifies validation steps to be pursued in upcoming work, including simulation, prototyping, and pilot testing.

II. Related Work

Advances in technologies such as the IoT, geospatial systems, and AI have driven digital transformation in agriculture, providing various applications for resource management, traceability, and decision support. However, the adoption of these technologies in agricultural auditing systems is still in its infancy, particularly regarding compliance with the CAP.

Akhter et al. [18] explore the implementation of sensors to optimise irrigation and input management, demonstrating the potential of the IoT for continuously collecting environmental and agronomic data. Jiang et al. [19] propose the use of satellite imagery and machine learning techniques for yield forecasting and plot monitoring, emphasising the importance of integrating geospatial data with predictive models.

In the field of audit and compliance management, Jiang et al. [19] also propose modular information system architectures for agricultural use, emphasising the importance of interoperability between technological components.

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Conversely, the literature emphasises the value of predictive analysis techniques in agricultural environments. Support Vector Machines (SVMs), Random Forests and artificial neural networks have successfully been used to anticipate anomalies, predict operational failures and estimate agricultural yields [20], [21]. Nevertheless, few studies have explored these approaches in the context of automated agricultural audit systems, representing a significant opportunity for innovation.

At the regulatory level, there is often a focus on the need for auditable, transparent systems that comply with standards such as the GDPR [22], [23]. Platforms that ensure data security and traceability of actions, as well as providing decision support based on objective data, are becoming increasingly valuable, particularly when it comes to allocating public subsidies.

Against this backdrop, this article proposes extending the existing platform to integrate IoT devices, predictive capabilities and offline operational support. This proposal represents a conceptual advance that addresses the gaps identified in the literature, and it is intended to serve as a basis for future development and validation phases.

III. Architectural Proposal

This proposal aims to strategically evolve a geospatial-based agricultural audit management platform by integrating IoT technologies, predictive analysis algorithms and optimised functionalities for field operations. The main objective is to anticipate and overcome the current challenges facing the sector: fragmented data collection; a lack of real-time monitoring; reactive detection of non-compliance; and difficulty with scalability in geographically dispersed contexts.

The proposed conceptual architecture is based on a modular, layered structure divided as follows:

1) Data Acquisition Layer (IoT and Field Input):

This proposal aims to strategically evolve a geospatial-based agricultural audit management platform by integrating IoT technologies, predictive analysis algorithms and optimised functionalities for field operations. The main objective is to anticipate and overcome the sector's current challenges, which include fragmented data collection, a lack of real-time monitoring, reactive detection of non-compliance, and difficulty with scalability in geographically dispersed contexts.

The proposed conceptual architecture is based on a modular, layered structure divided as follows:

The first layer is responsible for the continuous collection of data from various distributed sources. It includes environmental sensors, such as soil moisture, temperature and light intensity probes, which are installed on plots to monitor agricultural conditions. In addition, the dataset is enriched by aerial images obtained by drones and observational records collected by technicians using mobile forms.

Data transmission will follow a hybrid model: real-time streaming for fixed sensors via lightweight protocols such as MQTT and asynchronous data transmission by mobile devices via RESTful APIs. In regions where cellular connectivity is limited, long-range low-power communication technologies such as LoRa (Long Range) or LoRaWAN may be adopted to ensure reliable sensor data transmission with minimal energy consumption. This model ensures resilience and flexibility, particularly in areas with limited connectivity.

2) Processing and Storage Layer:

At the heart of the architecture is a centralised data infrastructure based on PostgreSQL with the PostGIS extension. This setup enables the efficient storage and management of both spatial and tabular data. This configuration enables quick queries of geographical information, parcel boundaries and audit data.

Predictive analysis will be performed by integrating machine learning libraries such as TensorFlow, Scikit-learn and PyTorch. Random Forests and SVM models will be employed to identify risk patterns and predict non-compliance based on anomalies detected in the collected data or inconsistencies in beneficiaries' statements.

The layer also incorporates data transformation, normalisation, and validation pipelines to ensure data quality and analytical readiness.

3) Presentation and Interaction Layer:

It defines the mechanisms of interaction between the system and its users. Interactive dashboards displaying predictive alerts, audit status and compliance indicators will be made available to technicians and managers. Dynamic maps developed with Leaflet.js will allow each audit to be spatially contextualised, highlighting critical or irregular areas.

A dedicated mobile application will be developed with support for offline operation and local data caching, as well as interfaces adapted to the realities of working in the field. Once an internet connection is re-established, data will automatically synchronise with the central server to ensure consistency and security.

Fig. *1* illustrates the proposed architecture, emphasising the three functional layers and their connections. The Data Acquisition Layer collects distributed and heterogeneous information, the Processing and Storage Layer centralises, interprets and models the data, and the Presentation and Interaction Layer transforms this into actionable knowledge. This modular structure ensures the system is scalable, interoperable and aligned with legal requirements such as the GDPR.

Security and GDPR compliance are central to this proposal. To ensure the protection of sensitive data and the traceability of actions, the following will be implemented: data encryption at rest and in transit, profile-based access control, multi-factor authentication and audit logs [22], [23].

The architecture will be implemented in phases:

- Phase 1: Prototyping – development of integration modules with sensors, data ingestion APIs, and predictive dashboards with synthetic data.
- Phase 2: Integration and Simulation – functional validation using historical audit data to test interoperability, model performance and system robustness.
- Phase 3: Field Validation – Pilot implementation in selected agricultural regions, with a collection of user feedback and iterative optimisation of the solution.

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This roadmap allows for a gradual and controlled adoption of the solution, promoting technological innovation without compromising operational continuity.

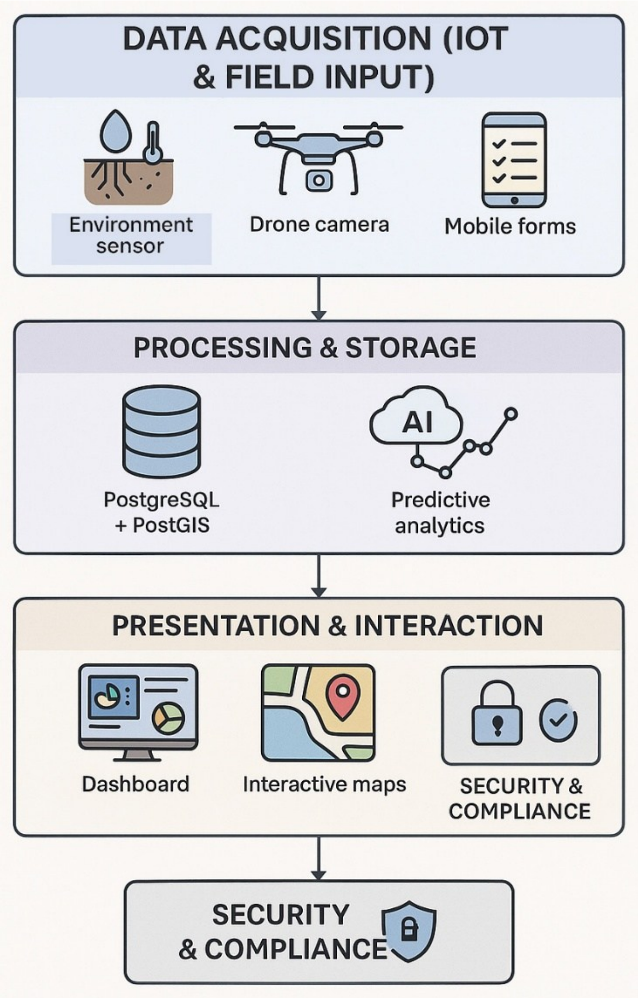

Fig. 1. Proposed architecture for the agricultural audit management platform.

A. *Functional Data Flow and System Logic*

The following section presents a detailed overview of the internal data flow and operational logic within the proposed system. It outlines how diverse data sources are processed, analysed, and transformed into actionable outputs. This breakdown highlights key functional stages, from ingestion and storage to predictive analytics, user interaction, and continuous system improvement:

1) Data Ingestion and Pre-processing:

The process begins in the Data Acquisition Layer, where IoT sensors continuously collect environmental variables such as soil moisture, temperature, and light intensity [10], [18]. These sensors, along with drone imagery and mobile forms filled by field technicians, generate both structured and unstructured data. Depending on connectivity, data is transmitted either in real time using MQTT or via asynchronous methods such as RESTful APIs. In low-connectivity regions, LoRa technology supports low-power, long-distance communication, ensuring data availability [11].

2) Integration into Central Storage:

Once acquired, the data is routed to the Processing and Storage Layer, where it is cleaned, validated, and harmonised. A PostgreSQL database enhanced with PostGIS handles geospatial and tabular data efficiently [19]. Metadata tags—such as sensor ID, timestamp, and plot location—enable traceability and cross-referencing. Data is stored in both raw and normalised formats to support future audits and analytics.

3) Predictive Analysis Pipeline:

After pre-processing, data enters the predictive analytics pipeline. Algorithms such as Random Forests and SVMs, known for their success in agricultural prediction tasks [20], [21], are applied to identify potential compliance risks. The models use both historical and real-time data to classify audit events, trigger alerts, and suggest prioritisation strategies. Model training and evaluation are conducted offline during development, with periodic updates informed by feedback loops and new data ingestion [12].

4) User-Facing Presentation and Alerts:

Outputs from the analytics engine are routed to the Presentation and Interaction Layer, where they are visualised in role-specific dashboards and interactive maps [4], [5]. Field technicians access real-time alerts and audit status through a mobile application with offline caching, while regional managers monitor system-wide KPIs and prioritise fieldwork based on model-generated risk maps. Data privacy and role-based access controls ensure secure and compliant interaction with the platform [22], [23].

5) Feedback and Iterative Learning;

User interactions—such as audit confirmations, corrections, or overrides—are fed back into the system to improve future model accuracy. This iterative loop aligns with continuous learning paradigms in AI systems and enhances the system's responsiveness over time [13].

This detailed flow ensures that each subsystem is decoupled, allowing for modular upgrades and simplified maintenance. The architecture supports scalability across heterogeneous agricultural contexts and embeds compliance with legal and ethical standards throughout the system. By tracing the transformation of raw inputs into actionable outputs, the section highlights how the proposed platform enables intelligent, data-driven decision-making across all operational layers.

IV. Discussion

This article presents an architectural proposal that offers a strategic and forward-looking response to the increasing complexity of agricultural audit requirements under the CAP. The system incorporates IoT technologies, predictive analytics and offline operating capabilities to transform the audit process into a proactive, data-driven and scalable mechanism.

As illustrated in Fig. *1*, the system's layered structure allows for modular implementation and straightforward adaptation to future technological advancements. Integrating field data collection with centralised processing and intelligent visualisation of results will substantially improve audit accuracy, speed, and reliability.

However, implementing this architecture involves anticipating several challenges. For example, limited network coverage in rural areas could compromise real-time data transmission, necessitating robust offline operating capabilities and asynchronous synchronisation mechanisms.

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Additionally, the costs and logistical complexity of installing and maintaining IoT devices on scattered farms may pose a barrier, particularly in regions with limited financial resources. Integrating heterogeneous sensors and ensuring data interoperability will require careful engineering and compliance with emerging standards in the context of IoT-based agricultural systems.

User adoption is another critical factor. For field technicians to use the platform effectively, the interface must be intuitive and responsive, and able to adapt to variable field conditions. Previous studies have emphasised the importance of user-centred design, adequate training and ongoing technical support when introducing digital tools into agricultural environments.

From a regulatory perspective, the proposal aligns with the European Union's strategic priorities: the European Green Deal and the Digital Europe Programme. The system architecture reflects the proposal's emphasis on transparency, traceability, and compliance with data protection regulations, particularly the General Data Protection Regulation (GDPR), through encrypted communications, profile-based access control, and comprehensive audit logs.

While this proposal is still in the conceptual stage, it sets out a clear and viable approach to modernising audit processes in the agricultural sector. Future development and validation are essential to test the system's performance, usability and scalability under real operating conditions.

While the proposed architecture remains at the conceptual level, its components and configuration are grounded in practices already validated in the literature. For instance, the selection of machine learning algorithms such as Random Forests and SVMs for risk prediction is supported by prior work demonstrating their accuracy in agricultural applications [20], [21]. Similarly, the adoption of communication protocols such as MQTT and LoRa is consistent with proven IoT strategies in rural contexts [10], [11].

To illustrate the feasibility of the system, a design-based validation was conducted using a synthetic scenario. In this scenario, mock sensor data—including soil temperature and humidity—was processed through the architecture's logical pipeline. These inputs, when analysed by pre-trained predictive models, generated alerts for non-compliance conditions. Although no physical deployment or dataset training occurred at this stage, the simulation confirms that the proposed components can operate in an integrated and actionable manner under the intended architecture.

A detailed performance evaluation, including accuracy metrics, system latency, and robustness tests, is planned for future work. These experimental phases will leverage real sensor data and feedback from pilot deployments to validate model behaviour and system responsiveness in operational settings. This stepwise strategy ensures that implementation proceeds with technical grounding while accommodating practical constraints and scalability considerations.

V. Technical Challenges and Risk Mitigation

The implementation of the proposed architecture involves overcoming several technical and operational challenges that could affect its effectiveness, scalability, and sustainability. This section describes the main risks identified and the strategies suggested for their mitigation, based on technical literature and established practices in the field of IoT and distributed systems management.

A. Connectivity Limitations and Offline Operation

Limited network coverage in rural areas remains one of the main obstacles to agricultural digitisation. Real-time data collection can be compromised by intermittent failures or a lack of coverage, especially in audits outside urbanised areas. The proposal addresses this risk by implementing offline capabilities in the mobile application, with automatic asynchronous synchronisation when the connection is restored. Strategies such as data compression, upload prioritisation and version conflict detection will be incorporated to robustify the process.

B. Reliability and maintenance of IoT devices

Environmental sensors used in agricultural contexts are subject to adverse conditions, such as humidity, dust, extreme temperature variations and mechanical interference. These factors can lead to reading errors, incorrect calibration or malfunctions. To mitigate this risk, priority will be given to using IP-certified sensors, implementing automatic integrity monitoring (self-checks) and setting up alerts for device failure. Additionally, preventive maintenance protocols and a periodic inventory of the sensor fleet should be established.

C. Security and Cyber Risks

Collecting and transmitting sensitive data, such as geospatial information, production data and beneficiary identifiers, exposes the system to the risk of intrusion, unauthorised access or data loss. The proposed architecture includes end-to-end encryption Transport Layer Security/ Secure Sockets Layer (TLS/SSL), strong authentication with session control, access segregation by profile and activity logging (audit logging). Additionally, regular security audits and penetration testing are recommended to detect vulnerabilities.

D. Interoperability between systems and sensors

The variety of devices and suppliers in the agricultural ecosystem can lead to compatibility issues. Such issues can compromise the efficient integration of sensors, databases and analytical modules. The proposal includes adopting open and interoperable standards such as the Open Geospatial Consortium SensorThings API, as well as formats such as GeoJSON or ISO 11783 (ISOBUS). It also involves using adaptive middleware to abstract technical differences between devices.

E. Operational Sustainability and Costs

In the long term, maintaining a robust IoT infrastructure and updating predictive models incurs financial and logistical costs. To ensure economic viability, a scalable, modular approach will be promoted, incorporating open-source components and partial operation. Using synthetic data for testing and automating machine learning routines will also help to reduce operating costs.

VI. Integration Scenarios and Use Cases

The versatility of the proposed architecture allows it to be adapted to different operational contexts within the scope of agricultural audits. This section presents three representative use cases, illustrating how different user profiles can interact with the system and the expected benefits in terms of efficiency, traceability, and decision-making.

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A. Field Technician – On-site Audit with IoT Support

During an audit visit to a farm, the field technician uses the platform's mobile application to access the previously synchronised digital file for the plot. On-site, they record observations, collect photographic evidence and validate data from installed sensors (e.g., soil temperature, humidity). If a possible non-compliance is detected, the system can generate an automatic alert based on values outside the expected parameters, using predictive models. Even in areas without internet, all data is stored locally and synchronised later with the central system.

B. Regional Manager – Real-Time Monitoring and Prioritisation

The regional audit manager uses the platform dashboard to get an overview of ongoing audits, including risk indicators for specific parcels or geographical areas. Using interactive maps, they can identify areas with a higher probability of non-compliance, as determined by machine learning models, and then reorganise field teams to prioritise the most critical audits. This approach enables dynamic resource allocation and greater effectiveness in meeting inspection requirements.

C. Regulatory Authority — Assessment and Reports for Decision Makers

The public authority responsible for CAP compliance can access automatic reports generated by the platform containing compliance metrics, audit history and KPIs. Data export features in interoperable formats facilitate integration with other national and European systems. Traceability of all actions ensures complete auditability by GDPR and administrative transparency requirements.

These cases each demonstrate the practical applicability of the architecture, its adaptability to different user profiles and its potential to improve transparency and efficiency in the auditing of agricultural processes.

VII. Ethical, Legal, and Sustainability Considerations

Integrating digital technologies, such as IoT sensors and AI models, into agricultural auditing systems raises important ethical, legal, and sustainability issues. These issues must be considered to ensure social acceptance, legal robustness, and alignment with sustainable development goals at the European and global levels.

A. Privacy and ownership of agricultural data

The continuous collection of sensitive data in the field, such as georeferenced images, crop conditions or compliance indicators, requires a data governance model that safeguards the rights of farmers and other involved parties. In line with the recommendations of the European Data Governance Act and the Code of Conduct for Data Sharing in Agriculture, farmers must retain control over the data generated on their farms. This includes the right to informed consent, data portability, and transparent access for processing purposes.

The proposed architecture includes mechanisms for registering consent, anonymising data and visualising the permissions granted, thereby promoting fairness and trust in the system.

B. Transparency and Algorithmic Fairness

Using predictive models to flag non-compliance or prioritise audits carries the risk of algorithmic bias, which could have an unfair impact on certain farms or regions. According to the OECD Principles on AI, algorithmic fairness requires mechanisms for explainability, model auditing and bias mitigation.

To ensure fair, understandable and auditable decisions, the proposed system will integrate model interpretation techniques (such as SHAP or LIME), performance reports by subgroups and cross-validations.

C. Regulatory Compliance and Legal Liability

Compliance with the GDPR forms a fundamental part of the system. The architecture incorporates data encryption in transit and at rest, profile-based access control, audit logs and data retention and deletion policies. Additionally, smart contracts and clear terms of service could reinforce the definition of responsibilities between parties, including sensor maintenance, the validity of collected data and the use of predictive outputs.

Future experimental validation will include a data protection impact assessment, as required by Article 35 of the GDPR.

D. Environmental and Technological Sustainability

The potential of digitalisation to promote sustainable agriculture is widely recognised, particularly in reducing the use of resources, improving water efficiency, and enabling real-time environmental monitoring. This proposal aligns with the objectives of the European Green Deal and the Farm to Fork Strategy, promoting more resilient and resource-efficient farming practices.

However, the environmental impact of the technology itself, such as the energy consumption of IoT devices and the carbon footprint of data centres, must be monitored. The proposal incorporates sustainable development practices, including the use of energy-efficient sensors, support for local solar energy and optimised AI models with low computational costs.

E. Data Governance and Ethical Standards

The ethical governance of data and intelligent systems will be based on principles such as data minimisation, technical interoperability, and organisational transparency. Adopting open standards, such as the OGC SensorThings API and the FAIR principles (Findable, Accessible, Interoperable, Reusable), will enable secure integration with European ecosystems and guarantee the ethical reuse of information.

Additionally, the platform will establish an ethical and technical council to oversee the evolution of algorithms, protect user rights, and ensure compliance with current standards.

VIII. Conclusion and Future Work

This article presents a conceptual architectural proposal for the evolution of an agricultural audit management platform that integrates IoT technologies and predictive analysis algorithms, as well as robust functionalities for field operations in areas with low connectivity. The proposal addresses gaps identified in the literature and practice, particularly concerning the need for intelligent, automated and scalable management of compliance with the CAP.

A modular architecture comprising three functional layers, data acquisition, processing and presentation, was designed based on an existing technological platform. The proposal incorporates advanced security mechanisms, interoperability

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and offline operation, along with analytical support based on machine learning. This ensures compliance with the GDPR and other relevant European standards.

Although no experimental deployment has been conducted at this stage, a design-based validation using synthetic data was performed to simulate the integration of sensor inputs, data processing pipelines, and predictive risk alerts. This conceptual validation aligns with widely accepted early-stage practices in distributed systems and IoT development, where full deployment is preceded by simulated environments to test architectural coherence and functional feasibility. The approach is further substantiated by prior studies that validate the same methodologies and technologies in similar agricultural contexts [10], [20], [21].

The usage scenarios presented demonstrate the applicability of the solution in different operational contexts, including for field technicians, managers and regulatory bodies. This reinforces its transformative potential. The ability to generate predictive alerts, conduct audits more efficiently and guarantee digital traceability could be critical in reducing operating costs, increasing coverage and improving the overall effectiveness of the agricultural audit system.

Strategically, this proposal aligns with European digitalisation and sustainability goals, including the European Green Deal, the CAP 2023 to 2027, and the Digital Europe programme. It also considers key ethical and legal issues, such as data protection, algorithmic fairness and environmental sustainability, thereby strengthening the robustness and legitimacy of the proposed solution.

The following stages are planned for future work:

1) Technical prototyping of data flows with real and synthetic sensors;
2) Training and validation of predictive models using historical datasets;
3) Pilot deployments in selected agricultural regions with iterative improvement based on user feedback;
4) Exploration of European funding under programmes such as Horizon Europe, the PRR or LIFE to support field-scale validation.

These steps will be essential for evaluating system feasibility, performance, scalability and usability under real-world constraints, thereby contributing to the digital transformation of agricultural audit systems.

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