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# Enabling semantic interoperability for smart farming

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**Abstract.** The strain on food security, environmental health, ecosystems, and fertile land, driven by a growing global population, can be alleviated through sustainable agriculture. To navigate this critical situation, it is essential to leverage existing technologies. The advent of the Fourth Industrial Revolution and the evolution of the internet have opened up new possibilities such as precision agriculture, IoT-based farming, and data-driven analytics for the agriculture sector. One promising approach is the utilization of semantic web technologies in smart farming. This article presents an ontology-based method designed to enable semantic interoperability across various smart farming systems. By merging and integrating existing domain ontologies, a unified framework is proposed, that facilitates seamless data exchange, enhances decision-making, and addresses key challenges in sustainable agriculture.

**Key words:** IoT, ontology, semantic interoperability, semantic web of things, smart farming.

## INTRODUCTION

As the world grapples with the twin challenges of food security and environmental sustainability, smart farming emerges as a promising solution to optimize the agricultural sector and advance the Sustainable Development Goals[1] (SDGs), particularly SDG 2 - Zero Hunger, SDG 13 - Climate Action, and SDG 15 - Life on Land, by enabling data-driven decision-making and increasing productivity (Swain et al., 2023). However, the lack of standardized data formats and shared vocabularies, also known as the semantic gap, has hindered interoperability across systems (Bökle et al., 2022). This gap refers to the challenge that arises when different systems interpret or represent the same data in incompatible ways, preventing seamless data exchange and integrated insights.

Ontologies can be seen as dictionaries for smart farming systems. They help computers understand the meaning of data and communicate effectively. This means systems can share information seamlessly, leading to better data analysis and smarter farming practices. These dictionaries can also help people from different backgrounds understand each other better, encouraging collaboration and innovation. However, as individual systems develop their own ontologies, interoperability becomes increasingly

[1] https://sdgs.un.org/goals

difficult. Bridging this semantic gap is essential for realizing the full potential of sustainable and intelligent agriculture (Osman et al., 2021a).

To address these challenges, a novel approach is proposed: merging and integrating the existing ontologies developed for diverse applications into a single, comprehensive one. This unified ontology will serve as a shared dictionary for all applications and systems, enabling seamless data exchange and collaboration, unlocking deeper insights through enhanced analysis, and fueling innovation by providing a common foundation for researchers and developers. This approach can unlock the transformative power of smart farming, revolutionize agricultural practices, and ensure a sustainable and secure food supply for our ever-growing population.

The remainder of this paper is structured as follows: Section 2 provides essential background on the Internet of Things, Smart Farming, and ontologies. Section 3 reviews the related works, outlining existing approaches and highlighting potential gaps. Section 4 outlines the design and methodology of the ontology merging process, including ontology selection and tool usage. Finally, Section 5 presents and discusses the results of the merged ontology and outlines promising avenues for future work.

## BACKGROUND

The Internet of Things (IoT) is a network of interconnected devices, enabling data collection and exchange (Thakur et al., 2023), thereby creating an intelligent ecosystem that autonomously interacts with the physical world in real-time (Yang et al., 2020). Since its inception at MIT in 1999, the IoT has undergone four distinct phases (Sciullo et al., 2022; Amara et al., 2022). Each phase reflects an evolution in the way devices connect, communicate, and share data. These developments have shaped the current landscape of smart farming, which relies heavily on IoT innovations:

- Phase 1: Connecting Things to the Internet, coined by Kevin Ashton in 1999, this phase focused on connecting objects via Radio Frequency Identification (RFID).
- Phase 2: Connecting Things to the Web, this phase solidified the Web of Things (WoT) architecture by 2010, leading to the development of the Social WoT (SocWoT) in 2013.
- Phase 3: Semantic WoT Starting in 2014, this phase focused on embedding meaning into device communication to allow systems to understand and act on shared data. This directly supports semantic interoperability, the core of this study.
- Phase 4: Standardized WoT Beginning in 2015, this phase concentrated on standardizing WoT applications through The World Wide Web Consortium (W3C) standards.

The application of IoT across different sectors adds the notion of ‘Smart’, leading to transformative changes (Lampropoulos et al., 2019). One of the most prominent examples is Smart Farming, where IoT applications optimize agricultural practices by monitoring soil conditions, managing irrigation, analyzing crop health in real-time, etc (Talero-Sarmiento et al., 2023).

### Smart Farming and precision agriculture

Smart farming and precision agriculture are closely related concepts, often used interchangeably, but they can have nuanced differences in their emphasis and scope.

Precision agriculture emphasizes optimizing existing processes through precise measurements and targeted interventions, for example, applying fertilizers only where needed using soil maps generated via he Global Positioning System (GPS) and Geographic Information Systems (GIS) (Keskin et al., 2016). Data collected through these technologies primarily informs decision-making within existing farm processes (Temizel et al., 2016). On the other hand, Smart farming takes a broader perspective, focusing on data access and application for holistic management by leveraging real-time data, AI, and IoT systems for adaptive decision-making. For instance, a smart farming system might combine soil moisture readings, weather forecasts, and crop growth models to automatically schedule irrigation across a farm.

In the rest of the paper, the broader concept Smart Farming will be used, as the aim is to merge various subdomains within this sector, thereby facilitating a seamless exchange of information among them.

### Ontologies: A Path to Unified Knowledge Representation

The ontology-driven approach is a methodology that leverages ontologies to address the challenges of semantic interoperability, enabling seamless communication and collaboration among diverse systems.

Ontologies are formal, machine-readable representations of knowledge in a specific domain. For example, in smart farming, an ontology may define concepts like 'SoilMoistureSensor', 'CropType', and 'IrrigationEvent', along with the relationships between them. This structured vocabulary ensures that different systems interpret and use data consistently (Gruber, 1993). They provide a structured framework for describing concepts, relationships, and constraints in a shared vocabulary. In this way, ontologies facilitate knowledge sharing and information exchange, ensuring that systems can exchange and interpret data with a consistent and meaningful understanding.

This consistent and meaningful understanding, fostered by ontologies, is essential for achieving semantic interoperability, paving the way for more intelligent and interconnected ecosystems.

## RELATED WORKS

The field of Semantic Web of Things (SWoT) has seen a surge of valuable contributions investigating the application of semantic technologies to enhance the functionality and performance of IoT systems, particularly within smart farming (Androcec et al., 2018; Rhayem et al., 2020; Pandey et al., 2021). This research area shows promise, with studies exploring ontologies in smart farming and their ability to enhance agricultural practices. These contributions aim to solve practical agricultural problems such as pest control, crop monitoring, irrigation scheduling, and livestock management (Drury et al., 2019).

Researchers have investigated ontologies in various smart farming applications. For example, (Khan et al., 2019) specifically addressed the needs of cotton farming by proposing a cotton crop cultivation-oriented semantic framework based on an IoT smart farming application. Additionally, (Chukkapalli et al., 2020) proposed an ontologydriven framework for attribute-based access control, addressing critical security concerns in smart farm ecosystems. Furthermore, (Sanjeevi et al., 2021) presented, a Hierarchical Model utilizing Ontologies (HMO-IoT) for accurate detection of post-harvest losses, specifically targeting Sekai-ichi apples. Moreover, (Symeonaki et al., 2022) developed an ontology-based IoT middleware approach for smart livestock management, enabling context-aware control of thermal environments in pig farms.

Beyond specific applications, research has also focused on enhancing the underlying middleware architecture for smart farming. Notably, (Gaire et al., 2013) extended the Global Sensor Network (GSN) to incorporate semantic capabilities, facilitating efficient data exchange and interpretation. Similarly, (Htaika et al., 2018) proposed a fully interoperable middleware framework by seamlessly integrating semantic web technologies with the existing GSN infrastructure. These collective efforts demonstrate the versatility of ontologies in empowering smart farming technologies and addressing critical challenges within the agricultural domain.

Although each individual system achieves internal interoperability, the broader smart agriculture ecosystem still faces significant challenges in interorganizational information integration. This stems from the diverse ontologies adopted by different stakeholders (applications), which act as barriers to data exchange and collaboration. The aim is to find a solution for the interorganizational integration. To the best of our knowledge, previous efforts to address this challenge have focused on either enriching existing ontologies like ONTAgri with Service-Oriented Architecture (SOA) (Fahad et al., 2021) or creating entirely new taxonomies and enriching it by classifying datasets based on sensors using machine learning (Lynda et al., 2023). While both approaches have merit, expanding an insufficient ontology like ONTAgri (Rehman & Shaikh, 2011) may not be the most effective solution, nor may creating a taxonomy from scratch, which can be time-consuming and resource-intensive.

These studies demonstrate how tailored ontologies can deliver domain-specific value, but also highlight the challenge: most ontologies are designed in silos, leading to fragmented and incompatible data ecosystems. This approach focuses on securing a seamless flow of data between all these systems, each of which is currently developing ontologies for its own use. This involves merging these ontologies using semantic web techniques. The goal is to apply the integration process to create one single ontology that gathers all necessary information for a comprehensive smart farming system, encompassing all sub-domains.

## Ontology Merging for Semantic Interoperability in Smart Farming

For a farm where every element share understanding of the information’s meaning and context, from irrigation systems to weather sensors, it’s essential for each device to share information seamlessly, thereby creating a unified understanding of the agricultural ecosystem. This is achievable through ontology interoperability, which is the ability of different systems to understand and interpret each other’s data.

Intra-organizational integration focuses on communication within a specific domain, such as irrigation. For example, ensuring interoperability between devices like sprinklers, soil moisture sensors, and flow meters is essential for optimizing water use and supporting healthy crop growth. By removing communication barriers within this subsystem, each component can contribute to a shared understanding of irrigation needs and act accordingly.

However, the true power of smart farming lies in inter-organizational integration. This involves bridging the gap between ontologies from different sub-domains within the broader smart farming ecosystem, like merging the irrigation ontology with the weather ontology. This allows systems to factor in weather data like precipitation and humidity, leading to smarter irrigation decisions. Bridging this semantic gap between subdomains through ontology merging is the main objective of this study. Fig. 1 illustrates these two types of integration.

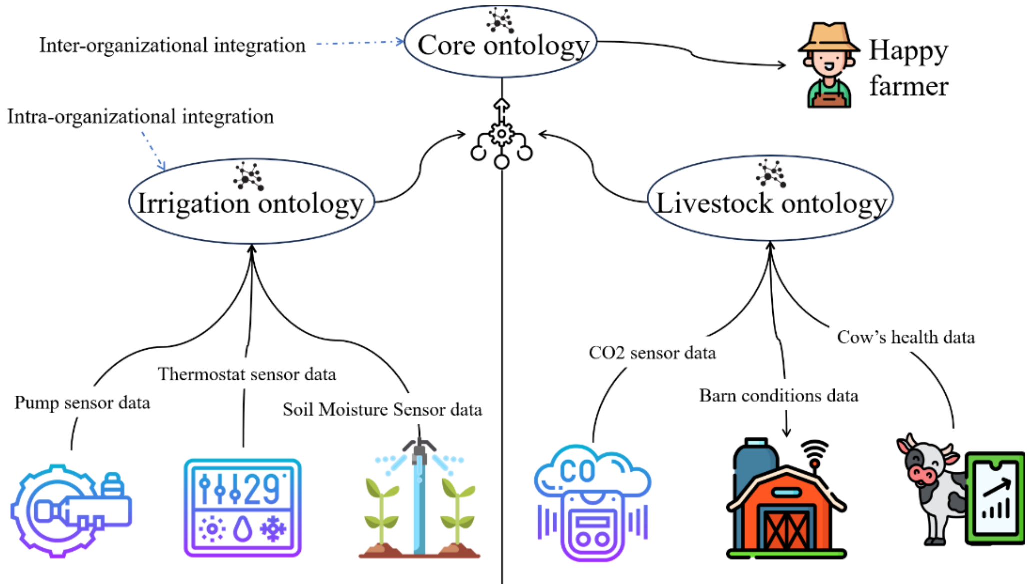


**Figure 1.** Semantic Interoperability in Smart Farming.

To overcome these challenges, a comprehensive approach is needed, based on ontology integration to identify and align terminology across different ontologies to ensure consistent communication.

**Core-Ontology for Smart Farming**

A core upper ontology aims to achieve maximum coverage of relevant concepts while maintaining minimal ambiguity. It offers several key benefits:

- Enhanced clarity and comprehensibility: A concise core ontology reduces redundancy and complexity, making it easier to understand and use.
- Increased interoperability: Minimizing ambiguity facilitates seamless integration with existing and future ontologies, fostering collaboration and data sharing.
- Efficient knowledge representation: By focusing on core concepts, the ontology allows for efficient storage, retrieval, and analysis of agricultural knowledge.

It paves the way for several exciting possibilities:

- Knowledge graph development: This core ontology serves as a robust foundation for building comprehensive knowledge graphs in the smart farming domain, facilitating knowledge discovery and analysis.
- Standardized data exchange: By promoting a shared vocabulary and data structures, the core ontology enables seamless data exchange between diverse smart farming systems and applications.

• Enhanced collaboration: A common ground for knowledge representation simplifies collaboration and knowledge sharing among researchers, developers, and practitioners within the smart farming community.

## MATERIALS AND METHODS

A core upper ontology is proposed for the smart farming sector, it is acquired by merging a set of carefully chosen ontologies (See subsection 4.2). This ensures comprehensive coverage of the smart farming domain while leveraging existing knowledge and expertise.

### Ontology Selection Rationale

To ensure comprehensive domain coverage and interoperability, ontologies were selected based on their relevance to core smart farming subdomains such as crop management, soil conditions, sensor data, environmental modeling, and plant physiology. The selection criteria included:

- Public accessibility
- Domain specificity and granularity
- Reuse in prior agricultural ontology projects.

### Set of ontologies:

Building upon the foundation of existing research (Arnaud et al., 2020; Bhuyan et al., 2022), and incorporating several recently developed ontologies (Goldstein et al., 2021), a comprehensive set of openly accessible ontologies was assembled for the merging process. Table A.1 (See Appendix A) provides an overview of these ontologies, highlighting the specific contributions they make towards the construction of the unified ontology. To address the limited availability of publicly accessible smart farming ontologies and increase efficiency, additional ontologies are introduced for the IoT and agriculture in general. Therefore, these new ontologiesw will be meticulously aligned with the existing smart farming ontologies to expand the available concept set. (Fig. 2 illustrates this).

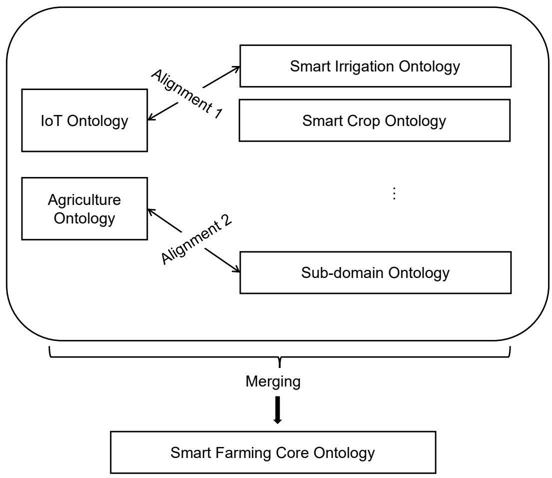


**Figure 2.** Ontological Bridge: Smart Farming, IoT, and Agriculture.

For example, SOSA and IoT-Lite were selected for their strong modeling of sensor data and observations, while the Agronomy Ontology and Plant Trait Ontology address farming practices and phenotypic traits.

**Ontology Merging Workflow**

The ontology integration involves two key steps: ontology alignment and ontology merging. Alignment focuses on identifying and expressing the correspondences between concepts in different ontologies. Merging then leverages this alignment to create a unified ontology by combining elements from the originals.

The available tools for ontology integration vary; some are capable of performing both alignment and merging, while others are specialized for only one of these tasks. Consequently, these tools often need to be used in combination to achieve comprehensive integration.

To select the appropriate tools, various existing research were reviewd. A recent review article (Osman et al., 2021a) provided a comprehensive comparison of ontology merging tools, guiding our choice of the most suitable option for the presented needs.

For merging, a tool capable of handling multiple ontologies simultaneously is required. Based on the aforementioned review, the 'Alignments Reuse for Ontology Merging' (AROM)[2] (Osman et al., 2021b) was selected. It offers two primary configurations for ontology merging: with or without pre-computed alignments. When alignments are provided, AROM leverages this information to identify equivalent entities across the source ontologies. This guided approach ensures a more semantically accurate merged ontology, where equivalent concepts are explicitly linked and redundancies are minimized. In the absence of alignments, AROM employs a simpler strategy of merging all entities from the input ontologies. This approach can be valuable for scenarios where the goal is to create a comprehensive knowledge base encompassing all information from the source ontologies, even if it might introduce some redundancy or inconsistency in the merged outcome.

Given the focus on achieving a coherent result that leverages interoperability, the alignment functionality of AROM was used. Therefore, for the alignment step, various publicly available tools[3] were reviewed, and top-performing tool according to the Ontology Alignment Evaluation Initiative (OAEI)[4]. The OAEI, held annually alongside the Ontology Matching workshop at the International Semantic Web Conference (ISWC)[5], rigorously evaluates alignment tools, ensuring access to the best solutions.

According to the comprehensive results from the OAEI 2023 (Pour et al., 2023), each tool has distinct strengths tailored to specific operational needs. LogMap (Jiménez-Ruiz et al., 2011) demonstrates superior performance in scenarios demanding fast processing and exceptional precision. This efficiency is crucial for this project requirements, where timely and accurate ontology matching impacts subsequent data analysis phases significantly. While ALIN (Pour et al., 2023) excels in enhancing recall in uncertain scenarios, the priority for the current application lies in maintaining high precision and processing speed, leading us to opt for LogMap as the most suitable tool for the presented needs. This decision is grounded in the empirical evidence provided by the OAEI 2023 results, which clearly highlight LogMap's capabilities in meeting this project's specific criteria.

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[2] https://github.com/inesosman/AROM
[3] https://tinyurl.com/public-oaei-systems
[4] https://oaei.ontologymatching.org
[5] https://iswc2023.semanticweb.org

Fig. 3 illustrates the impact of the alignment on the construction of the merged ontology. Using LogMap (Jiménez-Ruiz et al., 2011) contributes to a reduction in the number of concepts within the merged ontology.

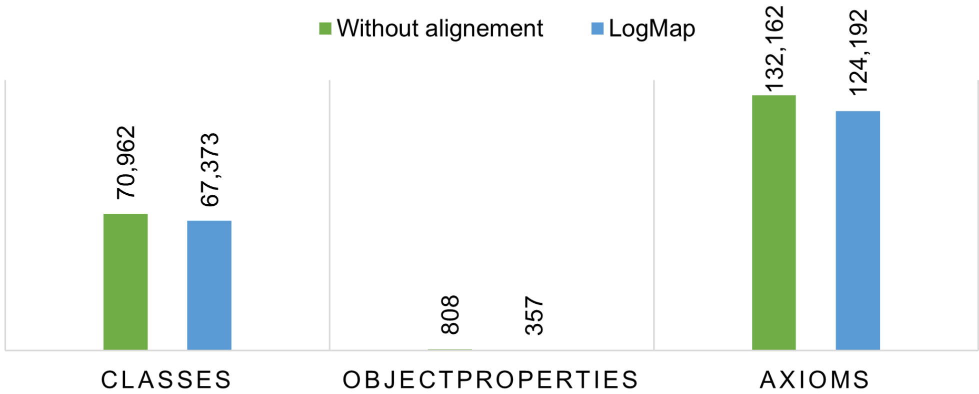


**Figure 3.** Impact of LogMap on the Structure and Composition of the Merged Ontology.

LogMap's configurable parameters, like matching thresholds and inconsistency repair (default: true), allow for tailored ontology matching. While the default settings were used for this experiment, exploring different configurations could potentially achieve a greater reduction in concepts while main taining accuracy and coherence, highlighting the importance of customizing LogMap for optimal results.

## RESULTS AND DISCUSSION

### Resulting merged ontology

The merged ontology resulting from the integration process is represented in the OWL 2 DL format. For the purpose of reading and opening this ontology, the Protégé[6] ontology editor was employed (See Fig. 4).

Our merged ontology construction process generated a comprehensive knowledge base, encompassing 67,373 classes, 357 object properties, and 124,192 logical axioms. As part of the technical validation, consistency checks confirmed its logical integrity, while the absence of unsatisfiable classes underscored its internal coherence. Annotations and labels are provided in English.

This rich structure positions the merged ontology as a powerful resource for future research and applications. The ontology is publicly accessible via an online repository[7].

Despite the technical success of the merging process, several critical limitations and trade-offs should be acknowledged:

- Complexity and Usability: The richness and breadth of the ontology result in a large number of concepts, which may complicate its use for practitioners, developers, or researchers who are unfamiliar with ontology engineering. Navigating the full structure or identifying relevant classes for specific queries could present a steep learning curve.

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[6] https://protege.stanford.edu

[7] https://github.com/NaoualSmaili/gistAgro

- Performance Considerations: The large number of classes and axioms may affect the performance of reasoning tasks and SPARQL queries, particularly in real-time or resource-constrained environments.

In terms of empirical validation, users can leverage SPARQL queries to interact with the ontology, enabling them to retrieve and analyse pertinent information that aids in critical decision-making processes. For instance, a farmer could ask: ‘Should I irrigate my wheat fields today given the current soil moisture and tomorrow’s rainfall forecast?’

- The ontology enables this question to be answered by connecting:
- Crop water requirements (via smart cropping ontology)
- Real-time soil data (via IoT sensor ontology)
- Rainfall predictions (via weather ontology).

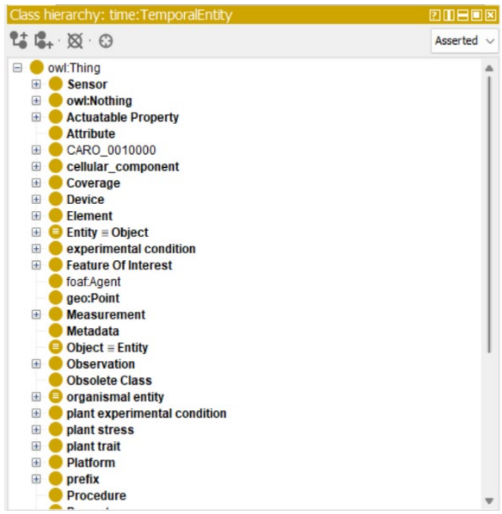


**Figure 4.** Overview of the resulting merged ontology: gistAgro.

This integrated reasoning goes beyond isolated data points and enables context-aware decisions, ultimately improving efficiency, sustainability, and yield (See Fig. 5).

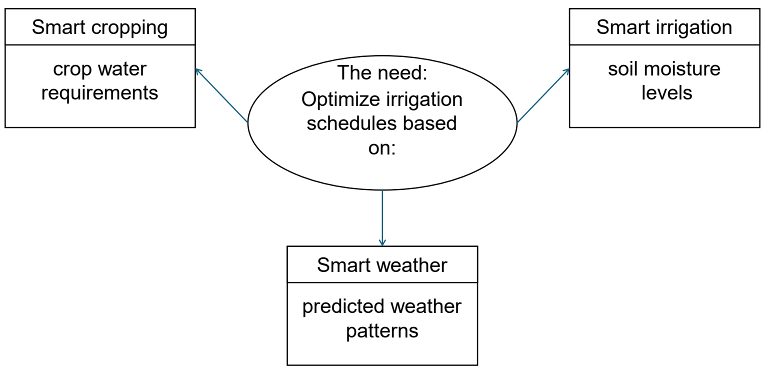


**Figure 5.** Example of a question the merged ontology is able to answer.

Once the work is complete (See Section Future works) the query for this question, illustrated in Fig. 6, will help decide whether irrigation should be done as soon as possible or delayed, and it highlights the capabilities of our ontology in integrating various smart farming sub-domains.

**Future works**

This work represents an important step toward enabling semantic interoperability in smart farming, but it is by no means the final stage. Several directions are planned to enhance and extend this contribution.

First, collaboration and access to additional ontologies from external researchers and domain experts are essential to enrich and refine the core ontology. We have actively reached out to members of the research community and remain hopeful that their contributions will help expand domain coverage and improve conceptual alignment. A detailed log of all updates and modifications will be maintained in the public GitHub repository to ensure transparency and traceability throughout the ongoing development process.

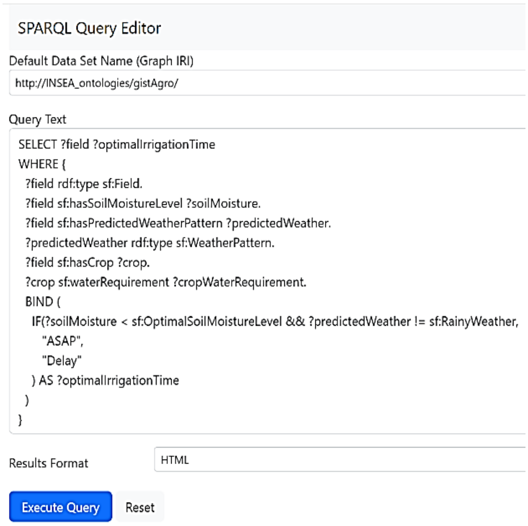


**Figure 6.** Example of SPARQL query.

In future versions, a rigorous validation will be conducted of the merged ontology using standard semantic metrics such as:

- Coverage ratio (extent of domain concepts captured)
- Consistency (logical coherence of ontology concepts)
- Completeness (degree to which essential domain knowledge is captured)
- Precision and recall (accuracy of alignments)
- Ontology reuse score, and
- SPARQL query performance (execution time and result relevance).

Additionally, publishing comprehensive documentation, tutorials, and query examples to assist third parties in effectively reusing and extending the ontology is planned.

However, we acknowledge that technical and social challenges remain. Merging heterogeneous ontologies may introduce conceptual overlaps and inconsistencies that require careful reconciliation.

On the social side, encouraging widespread adoption will depend on ease of use, alignment with existing standards, and clear demonstration of benefits to end-users in agriculture and agro-tech industries.

Finally, we emphasize that effective querying and evaluation of the ontology will greatly benefit from the active participation of smart farming specialists, whose domain insights will be invaluable in refining both structure and content.

## CONCLUSIONS

This paper presents a semantic interoperability framework for smart farming based on the integration of multiple existing ontologies. This approach addresses a critical challenge in smart agriculture: the fragmentation of knowledge across systems, which prevents seamless data sharing and automated reasoning.

By merging a diverse set of well-established ontologies into a unified core (gistAgro), a shared vocabulary is provided that enables intelligent data exchange across subdomains such as weather monitoring, soil analysis, crop planning, and irrigation control.

We believe that this work represents a significant contribution to the field of smart farming by addressing the critical challenge of semantic interoperability and paving the way for more efficient, integrated, and intelligent smart farming systems.

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APPENDIX 1.

This table catalogs the publicly available ontologies related to smart farming that were found and used in the merging process. It categorizes them based on their specific contribution to this unified ontology. Each entry includes the ontology's name, its URL for easy access, and the latest version that was used.

**Table 1.** Ontologies Merged to Enhance Data Interoperability in Smart Farming

| Ontology | Contribution to Unified Ontology | URL | Version |
|---|---|---|---|
| Bermudez-Edo et al. (2017) IoTLite | IoT Devices & Protocols | http://iot.ee.surrey.ac.uk/fiware/ontologies/iot-lite | 04/06/2017 |
| Janowicz et al. (2019) SOSA: Sensors, Observations, Samples, and Actuators Ontology | Sensors & Observations | https://github.com/w3c/sdw/blob/gh-pages/ssn/integrated/sosa.rdf | 10/08/2018 |
| Aubert et al. (2017) Agronomy Ontology | Agriculture & Farming Practices | https://bigdata.cgiar.org/resources/agronomy-ontology | 10/06/2020 |
| Chavez Feria & Poveda Villalón (n.d.) Sensor Data ontology | Sensor Data Management | https://bimerr.iot.linkeddata.es/def/sensor-data/ | 17/06/2021 |
| Buttigieg et al. (2016) Environment | Environment & Ecosystems | http://environmentontology.org | 11/07/2022 |
| Walls et al. (2019) Ontology Plant Ontology | Plant Anatomy & Growth | http://browser.planteome.org/amigo | 02/11/2022 |
| Cooper et al. (2024) Plant Experimental Conditions Ontology | Plant Experimentation | http://obofoundry.org/ontology/peco | 14/12/2022 |
| Cooper et al. (2020) Plant Trait Ontology | Plant Phenotypes & Traits | http://obofoundry.org/ontology/to | 13/02/2023 |
| Meier et al. (2018) Plant Stress Ontology | Plant Stress & Resilience | https://github.com/Planteome/plantstress-ontology | 13/07/2023 |
| Aleksander et al. (2023) Gene Ontology | Gene Function & Products | https://geneontology.org | 09/08/2023 |
| Gkoutos et al. (2012) Units of measurement ontology | Measurement & Units | http://obofoundry.org/ontology/uo | 07/09/2023 |
| Bada & Eilbeck (2012) Sequence Ontology | Biological Sequence Features | http://www.sequenceontology.org | 14/11/2023 |