Knowledge Graph for Intelligent Farming and Crop Monitoring

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***Abstract*—Precision agriculture generates diverse datasets across soil chemistry, weather, and crop yield that often remain isolated, limiting integrated analysis. This work develops a semantic framework using OWL 2 and SWRL to enable dynamic inference over agricultural data from the Kellogg Biological Station Long-Term Ecological Research (KBS LTER) site. Three datasets spanning 2011–2024 are integrated: agronomic yield records, soil chemistry measurements (pH, nutrients, organic matter), and weather observations (precipitation, temperature). Data are modeled using the SOSA ontology, with yield observations linked to soil and weather context through year-based temporal alignment. SWRL rules enable automated inference for nutrient deficiency detection, yield-limiting conditions, and management recommendations. The outcome is a knowledge graph supporting data-driven agricultural decision-making, demonstrated through a prototype system providing reasoning-driven recommendations for fertilizer management and crop planning.**

***Index Terms*—Semantic Web, OWL 2, SWRL, SOSA, Crop Ontology, Smart Farming, Crop Monitoring, Reasoning Systems, Precision Agriculture**

I. Introduction

Farming creates large-volume sensor, prediction, and farm activity data now. Such heterogeneous sources of data convey rarely interoperable information. **This project is motivated by the need to support sustainable practices such as crop rotation, determining which crop should follow another to improve soil fertility, minimize pest recurrence, and enhance yield.**

The Semantic Web technologies convey the fix to this issue by making ideas formalized and linking data. The project encodes knowledge on farms in OWL 2 and encodes decision rules in SWRL. The project reuses and realigns the available ontology SOSA (Sensor, Observation, Sample, and Actuator) for observation, allowing all measured values, such as soil nutrients, pH, yield, and weather indicators, to be modeled as standardized SOSA observations linked to the plot as the feature of interest, thereby improving integration, reasoning, and extensibility.

The combined graph enables dynamic decision-making, such as delaying fertilization during rain-prone periods or recommending crop rotations that break pest cycles and restore soil nutrients. **Previous works have largely focused on isolated domains such as soil chemistry or irrigation; this project extends those ideas by integrating multiple datasets of agronomic yield, soil chemistry, and weather records to provide holistic reasoning for intelligent crop rotation and resource optimization.**

Application Focus: The final outcome is a prototype web application that allows users to query and visualize integrated soil, weather, and crop data through an interactive dashboard. The app provides reasoning-based recommendations on optimal crop rotation sequences, fertilizer timing, and risk mitigation. Key features include knowledge graph exploration, SWRL-driven recommendations, and visualization of environmental trends.

II. Related Literature

Semantic Web technologies are now being used in agriculture to connect data from sensors, weather systems, and farm operations to support better decision-making. Agriculture generates vast amounts of data about soil, weather, crops, and pests, but this data often exists in separate systems that do not communicate with one another. Earlier research has developed smaller ontologies focused on individual areas, such as soil, irrigation, or pest management. This project aims to build on those foundations and combine them into a single, integrated reasoning framework that brings together multiple aspects of farming.

Haller *et al.* [1] and W3C/OGC [11] introduced the SOSA/SSN ontology, which provides a standard way to represent sensors, observations, and environmental features. This framework is used in this project to describe soil and weather data consistently, allowing observations from different devices to be compared and reasoned over. It forms the foundation for representing sensor-based data.

AGROVOC, developed by Subirats-Coll *et al.* [2] and Caracciolo *et al.* [3], is a multilingual vocabulary maintained by the Food and Agriculture Organization (FAO). It ensures consistent labeling of agricultural terms such as crops, fertilizers, and farming practices. In this work, AGROVOC terms are used to tag and interlink all the major agricultural concepts, which helps maintain consistency and promotes knowledge sharing across systems.

Arnaud *et al.* [4] and Matteis *et al.* [5] created the Crop Ontology (CO) to standardize crop traits and variables used in research and breeding programs. Incorporating CO allows the ontology to represent traits such as nutrient needs, growth cycles, and rotation patterns. This supports reasoning about relationships like how legumes help improve nitrogen levels or how cereals should be rotated to reduce pest risks.

The Environment Ontology (ENVO) [10] provides definitions for soil and land-use types that describe the environmental context of farms. Using ENVO allows this ontology to connect farming activities with environmental data, supporting spatial and ecological reasoning without the need to invent new soil classifications.

Kessler *et al.* [6] developed an ontology-based decision-support system for nitrogen fertilization using OWL and SWRL reasoning. Their work demonstrated that logical rules could turn soil test data into fertilizer recommendations. The proposed ontology follows this reasoning approach but extends it beyond nitrogen to include other nutrients such as phosphorus and potassium. It also combines soil, weather, and pest data to produce more adaptive recommendations.

Alharbi *et al.* [7] designed an ontology-based pest management system that uses environmental and biological indicators to assess pest risks. While their work focuses on detection and diagnosis, this project expands on it by connecting pest risk to soil conditions and crop types. This enables preventive decision-making, such as adjusting fertilizer schedules or changing crop rotation to minimize future infestations.

Jonquet *et al.* [8] presented AgroPortal, a repository for agricultural ontologies that promotes reuse and alignment between different models. Aligning the current ontology with AgroPortal ensures that it can interoperate with other ontologies and remain accessible to the wider research community.

Finally, de Vaulx [9] and ETSI [12] introduced SAREF4AGRI, which connects sensors, actuators, and decision systems for agriculture. Their work focuses on modularity and device integration. This ontology builds on that approach, integrating real-time observation data with reasoning-based recommendations for fertilizer and crop management.

Together, these studies establish a strong base for semantic modeling in agriculture, but each focuses on a specific area. This project takes a broader approach. It integrates soil properties, weather data, crop characteristics, and pest risks into one framework that can reason over real-world data. By combining established ontologies like SOSA, the model enables both fertilizer optimization and crop rotation planning, offering a more complete view of smart farming.

III. Problem Definition

Independent soil, weather, crop, and pest information currently preclude comprehensive, cross-domain decision-making. Most existing approaches focus on single domains, resulting in limited interoperability, low-quality cross-domain inference, and misaligned vocabularies.

The objective of this work is to develop an integrated, reasoning-ready model that:

- Integrates four key dimensions: soil properties, weather signals, crop characteristics, and pest hazards.
- Imports and aligns established ontologies such as SOSA to ensure semantic interoperability.
- Employs OWL 2 in combination with SWRL to automatically infer agronomic activities such as crop rotation initiation and fertilization delays based on forecasted rain and soil conditions.
- Provides fertilizer optimization and crop rotation recommendations from a unified knowledge graph to enhance reuse and transparency across systems.

A. Representative Use Cases

1) **Crop Rotation Recommendation:** Infer the next optimal crop to cultivate based on soil nutrient status and historical yield data (e.g., legumes following cereals to restore nitrogen).
2) **Fertilizer Optimization:** Recommend appropriate timing or postponement of fertilizer application using soil nutrient levels and rainfall forecasts.
3) **Pest Risk Mitigation:** Identify potential pest recurrence by linking crop type, soil, and climate data, then suggest rotations that break pest cycles.

IV. Proposed Approach and High-Level System Design

The project follows a structured, phase-based methodology that integrates ontology engineering, data transformation, reasoning, and query-driven visualization within a unified semantic framework.

A. Phase-wise Development Plan

- **Phase 1 – Ontology Design:** Develop the OWL 2 ontology defining classes like `Plot`, `Crop`, `SoilMeasurement`, and `WeatherSummary`, `YieldRecord`, `Recommendation`. Observation-related components are realigned with the SOSA ontology to standardize how soil, yield, and weather measurements are represented.
- **Phase 2 – Data Integration:** Collect and preprocess yield, soil, and weather datasets. Transform tabular CSV attributes (e.g., plot identifiers, crop types, nutrient values, rainfall summaries) into RDF triples using Ontotext Refine. Populate the knowledge graph according to the ontology's domain–range constraints and SOSA-aligned observation structure.
- **Phase 3 – Reasoning Implementation:** Encode SWRL rules for crop rotation and fertilizer scheduling based on soil nutrients and rainfall trends to infer agronomic knowledge such as next-season crop recommendations based on nutrient depletion and yield patterns, fertilizer postponement based on rainfall forecasts, and more. OWL 2 reasoning is used to classify entities and support rule execution.
- **Phase 4 – Query Processing and Application Interface:** Implement a lightweight Flask-based interface that

queries the ontology using SPARQL to retrieve SWRL-inferred recommendations, joins soil, crop, yield, and weather observations, and presents reasoning results in a user-friendly format. SPARQL acts as the retrieval layer for all inference outputs.
- **Phase 5 – Testing and Validation:** Validate inferred recommendations using scenario-based tests. Evaluate SPARQL query correctness, reasoning consistency, and cross-domain integration accuracy across soil, crop, and weather datasets.

B. System Architecture Overview

The system consists of four logical layers:

- **Data Layer:** Stores raw CSV data for soil, yield, and weather.
- **Ontology Layer:** Hosts the OWL 2 knowledge graph with aligned SOSA ontology.
- **Reasoning Layer:** Executes SWRL rules and SPARQL queries to infer insights like next crop recommendations and fertilizer scheduling.
- **Application Layer:** Exposes a Flask-based dashboard for user interaction and visualization.

C. Ontology Design Summary

The ontology defines relationships between `Plot`, `Crop`, `Treatment`, and corresponding observation records. Object properties such as `aboutPlot`, `forCrop`, and `withTreatment` interconnect the domains, while datatype properties like `soil_pH`, `soil_N_mgkg`, and `yieldKgPerHa` store empirical data. This design enables inferencing over temporal and contextual agricultural data, improving interoperability and reasoning outcomes.

D. Roles and Responsibilities

- **Arjun Harish:** Built the frontend dashboard and integrated the Flask API to visualize soil, yield, weather, and recommendation outputs.
- **Dhairya Kamalia:** Designed and validated the OWL 2 ontology, including class hierarchy and SOSA-aligned object/datatype properties.
- **Kavya Parekh:** Generated RDF triples and performed CSV-to-RDF data integration using Ontotext Refine to produce the TTL dataset.
- **Raj Mani Mitresh Mani:** Implemented SWRL rules and backend logic for inference-driven recommendations.
- **Samanvitha Patel:** Developed and optimized SPARQL queries and integrated them into the backend query pipeline.

V. Ontology Design

The proposed knowledge graph as shown in Fig. 1 is implemented in OWL 2 and organized around a small set of core agricultural concepts. The ontology is designed to be both reasoning–ready and aligned with the SOSA (Sensor, Observation, Sample, and Actuator) ontology so that future sensor data can be integrated consistently.

A. Ontology Structure and Core Classes

The conceptual model captures four main domains: plots, crops, soil, weather, and derived recommendations.

- **Plot** represents an experimental field unit or subplot. Individual plots are identified by treatment–replicate combinations (e.g., T1_R1).
- **Crop** encodes the crop grown on a plot in a given year; specialized subclasses such as *CerealCrop* and *LegumeCrop* support crop-rotation rules.
- **Record** is an abstract superclass for all measurement records and is modeled as a subclass of `sosa:Observation`. Its main subclasses are:
  - **YieldRecord** – yearly yield per plot.
  - **SoilMeasurement** – soil nutrient and physico-chemical properties.
  - **WeatherSummary** – aggregated weather features such as total rainfall and average temperatures.
- **Recommendation** represents the outcome of reasoning. It is specialized into *CropRotationRecommendation*, *FertilizerRecommendation*, and *PestManagementRecommendation*.

These classes are connected using object properties such as `aboutPlot` (linking any `Record` to the `Plot` it refers to), `forCrop` (linking a `YieldRecord` to the cultivated `Crop`), and `usesSoilMeasurement`, `usesWeatherSummary`, and `usesYieldRecord` (linking a `Recommendation` instance to the evidence on which it is based).

Numeric and textual attributes are modeled using datatype properties. Examples include soil chemistry properties (e.g., `soil_pH`, `soil_N_mg_per_kg`, `soil_P_mg_per_kg`, `soil_K_mg_per_kg`), yield indicators (e.g., `yield_kg_per_ha`), and weather features (e.g., `forecastRainfallAmount_mm`). Temporal context is captured via `hasYear`.

B. Alignment with SOSA Observation Pattern

To ensure interoperability, all measurement records in the ontology are aligned with SOSA:

- `Record` is a subclass of `sosa:Observation`.
- `Plot` is modeled as a `sosa:FeatureOfInterest`.
- Soil and climate characteristics such as pH, nitrogen, and rainfall are represented as subclasses of `sosa:ObservableProperty`.

This alignment enforces a consistent observation pattern in which each measurement (observation) is associated with a feature of interest (plot), an observable property (e.g., soil pH), and a literal value. As a result, the model can be extended with additional sensor streams with minimal redesign.

C. SWRL Rule Base

Domain logic is captured using SWRL (Semantic Web Rule Language) rules defined over the ontology vocabulary. The rules are encoded in the Turtle file as SWRL axioms and operate on soil, yield, and weather observations to generate recommendation instances. Representative rules include:

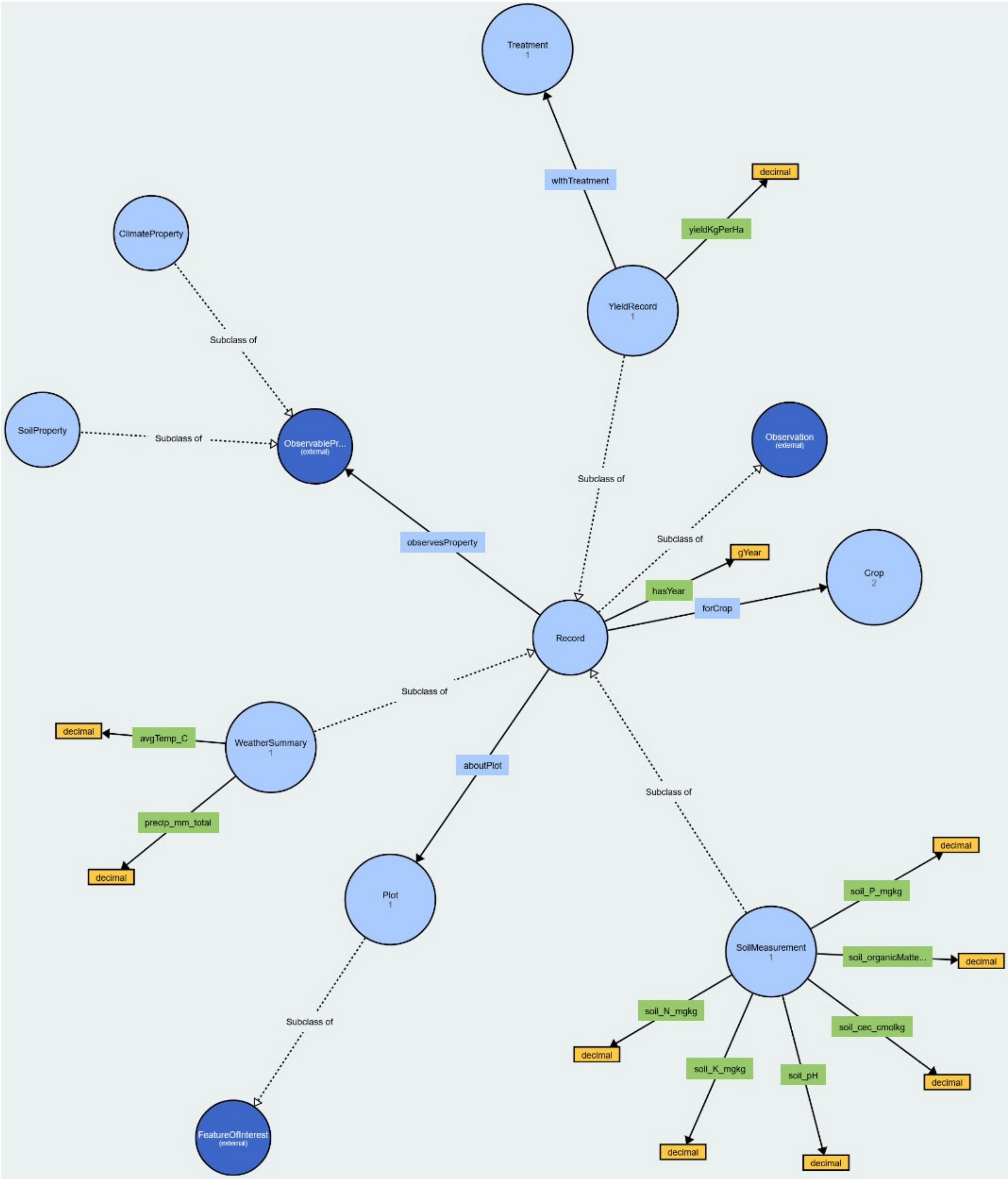

Fig. 1. OWL Ontology Design for Knowledge Graph–based Intelligent Farming System

- **Crop rotation rule:** if a plot grew a cereal crop in the current year and the associated soil nitrogen measurement is below a threshold, then assert a `CropRotationRecommendation` that recommends a legume crop for the next season.
- **Fertilizer postponement rule:** if soil nutrients are ade-

quate but the forecast rainfall amount exceeds a specified limit, then assert a FertilizerRecommendation whose action is "postpone" to avoid nutrient leaching.
- **Nutrient deficiency rule:** if a soil measurement shows phosphorus or potassium below agronomic thresholds, then assert a fertilizer recommendation for the corresponding nutrient.

Each rule combines ontology classes and datatype properties (e.g., soil_N_mg_per_kg, yield_kg_per_ha, forecastRainfallAmount_mm) using SWRL built-ins such as swrlb:lessThan or swrlb:greaterThan.

D. RDF/Turtle Instance Representation

Instances from the experimental dataset are materialized in an RDF graph using Turtle syntax. For each year and plot combination, the graph contains:

- a Plot individual (e.g., sf:Plot_T1_R1);
- a YieldRecord with yield_kg_per_ha and links to the plot and crop;
- one or more SoilMeasurement instances capturing soil chemistry for that plot and year;
- a WeatherSummary instance with rainfall and temperature statistics.

After reasoning, additional Recommendation individuals are added to the same graph, linking back to the evidence records via the object properties described above. This unified graph is the basis for all query operations described in the following sections.

VI. Data Collection and Processing

A. Data Sources

Three primary datasets are utilized:

1) **KBS LTER Agronomic Yield Dataset (1989–2024):** Contains yearly yield records for different crops across six agronomic treatments (T1–T6) with six replicates each. [13]
2) **KBS Soil Chemistry Dataset (2025):** Provides laboratory measurements of soil pH, nutrients (P, K, Ca, Mg), cation exchange capacity (CEC), and organic matter across nine fertilization treatments (F1–F9) with six replicates. [14]
3) **NOAA GHCN-Daily Weather Data for Gull Lake Biological Station (1989–2024):** Daily summaries of precipitation and temperature from weather station USC00203504, located at the Gull Lake Biological Station approximately 15 km from the KBS LTER site. This station was selected as it is the nearest high-quality, long-term weather monitoring station with complete coverage for the study period, providing the climatic context for the experimental plots. [15]

B. Data Preparation and Processing

The three datasets were preprocessed and integrated for the period 2011–2024, representing the overlapping temporal coverage. Key preprocessing steps include:

- **Temporal filtering:** All datasets restricted to years 2011–2024 to ensure temporal alignment.
- **Soil data aggregation:** Annual site-wide mean values calculated for soil properties (pH, P, K, Ca, Mg, CEC, organic matter). Missing years were forward-filled using the most recent available measurements, with a provenance flag (Soil_Measured) to distinguish actual measurements from propagated values.
- **Weather data aggregation:** Daily observations aggregated to annual summaries (total precipitation, mean maximum and minimum temperatures).
- **Unit standardization:** Precipitation converted from inches to millimeters; temperature converted from Fahrenheit to Celsius; yield standardized to kg/hectare.
- **Integration strategy:** Datasets merged using *Year* as the sole join key, treating soil and weather as site-wide annual environmental context for plot-level yield observations.

It is critical to note that the yield experiment treatments (T1–T6) and soil experiment treatments (F1–F9) represent independent experimental designs and are *not* mapped to each other. Soil and weather variables provide uniform annual environmental conditions shared across all yield plots, while treatment and replicate structure is preserved within the yield data.

After preprocessing, the integrated dataset is modeled using the SOSA ontology. YieldRecord, SoilMeasurement, and WeatherSummary are all represented as subclasses of sosa:Observation through the intermediate Record class. Individual attributes such as pH, N, P, K, and rainfall are modeled as sosa:ObservableProperty. During RDF generation, Plot identifiers are constructed from the Treatment_Replicate combinations (e.g., T1_R1), although this naming convention is external to the ontology.

C. Scope and Exclusions

Pest-specific and irrigation datasets are excluded due to incomplete data availability and temporal misalignment. Irrigation status is recorded in the soil dataset but not utilized in the current integration. Future work can incorporate direct pest observation data and fine-grained irrigation records as additional SOSA observation types.

VII. Implementation

The implementation consists of a reasoning pipeline over the OWL 2 ontology, a SPARQL query layer, and a lightweight web service that exposes recommendations to end users.

A. Reasoning Pipeline

The reasoning workflow is executed in two stages. First, an OWL 2 reasoner is used to classify the ontology and check that all instances are consistent with the class hierarchy and property restrictions. Second, the SWRL rule base described in Section V is applied to the populated graph. The rules derive new triples that instantiate Recommendation classes and attach them to the relevant plots, crops, and observation records.

The output of this pipeline is a single RDF graph that contains both the original data (plots, soil, weather, and yield) and all inferred recommendations. This graph is serialized in Turtle and loaded by the query layer.

B. SPARQL Query Layer

To retrieve insights from the knowledge graph, we define a set of parameterized SPARQL queries. Each query corresponds to one of the target use cases:

- **Next-crop recommendation query:** returns, for each plot and year, the recommended next crop inferred by the crop rotation rules.
- **Fertilizer optimization query:** selects plots for which the reasoning engine inferred a fertilizer postponement or nutrient deficiency recommendation, together with the supporting soil and weather observations.
- **Pest risk query:** retrieves plots where repeated crop patterns and weather conditions imply elevated pest recurrence risk.

These queries are implemented in a Python helper module and executed against the in-memory RDF graph using a SPARQL engine. Query results are converted to JSON structures that can be consumed by the web application.

C. Flask-Based Web Service

The application layer is implemented as a lightweight REST service using Flask. When the service starts, it loads the ontology and instance graph, runs the reasoning pipeline, and keeps the resulting graph in memory. The service exposes endpoints such as:

- /api/recommendations/next-crop – returns the next crop recommendation per plot;
- /api/recommendations/fertilizer – returns fertilizer actions (apply, postpone, or adjust rate);
- /api/recommendations/pest-risk – lists plots with high predicted pest risk;
- /api/plots/<id> – retrieves the soil, weather, and yield history for a given plot.

Each endpoint internally invokes one or more SPARQL queries and returns the results as JSON. A simple HTML/JavaScript front-end or notebook client can consume these endpoints to visualize time series and recommendations for specific plots.

D. Execution Environment

All components are implemented in Python 3 using standard Semantic Web libraries for RDF, OWL, SWRL, and SPARQL processing. The system can run locally without an external triple store by loading the ontology and instance data into an in-memory graph; however, the design is compatible with deployment on a dedicated RDF store or graph database if larger datasets need to be supported in future work.

VIII. Evaluation and Results

The evaluation of the proposed ontology-driven Smart Farming Recommender focuses on three aspects: (1) correctness of SWRL reasoning outputs, (2) accuracy of SPARQL-based data retrieval, and (3) usability of the interactive dashboard interface. All tests were performed using historical soil, weather, and yield data across plots T1–T4 for years 2012–2024.

A. Correctness of Reasoning Output

SWRL rules were validated by examining inferred recommendations for representative plot-year combinations. As shown in Fig. 2, the system correctly identifies a high pest risk for Plot T3_R1 in 2017 and recommends a legume crop (*Glycine max L.*) for the next season based on nitrogen depletion patterns and cereal rotation rules. This validates the correct firing of crop-rotation and pest-risk rules.

Similarly, for Plot T4_R5 in 2020 (Fig. 3), the system detects both high pest recurrence risk and insufficient phosphorus levels. As a result, the recommender issues a “Needs Fertilizer” alert alongside the recommended crop rotation. These findings confirm that SWRL logic consistently generates domain-appropriate agronomic decisions.

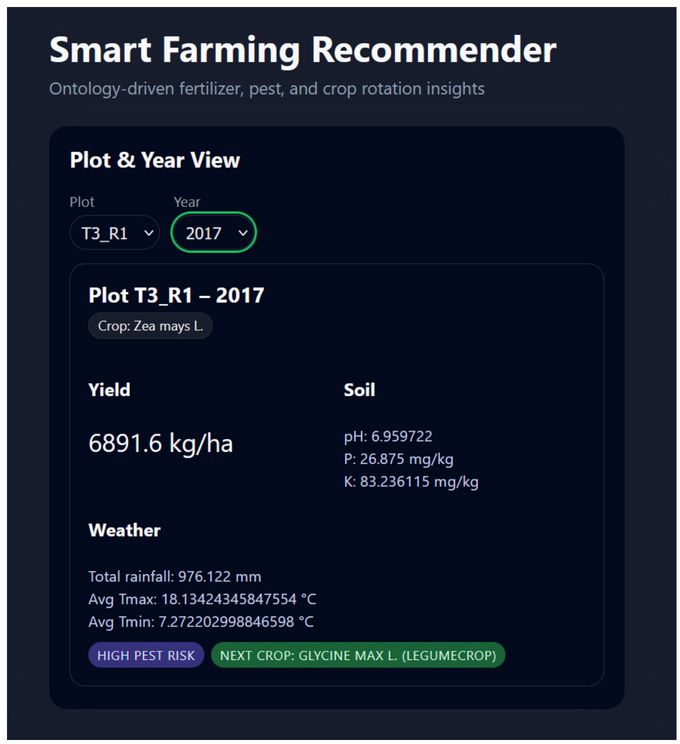

Fig. 2. Reasoning results for Plot T3_R1 in 2017 showing yield, soil metrics, rainfall summary, and inferred next-crop recommendation.

B. Cross-Domain Integration Accuracy

To assess integration fidelity, SPARQL queries were evaluated for correctness in retrieving plot identifiers, valid years, and associated observations. As shown in Fig. 4, the system automatically populates the year selector with all available

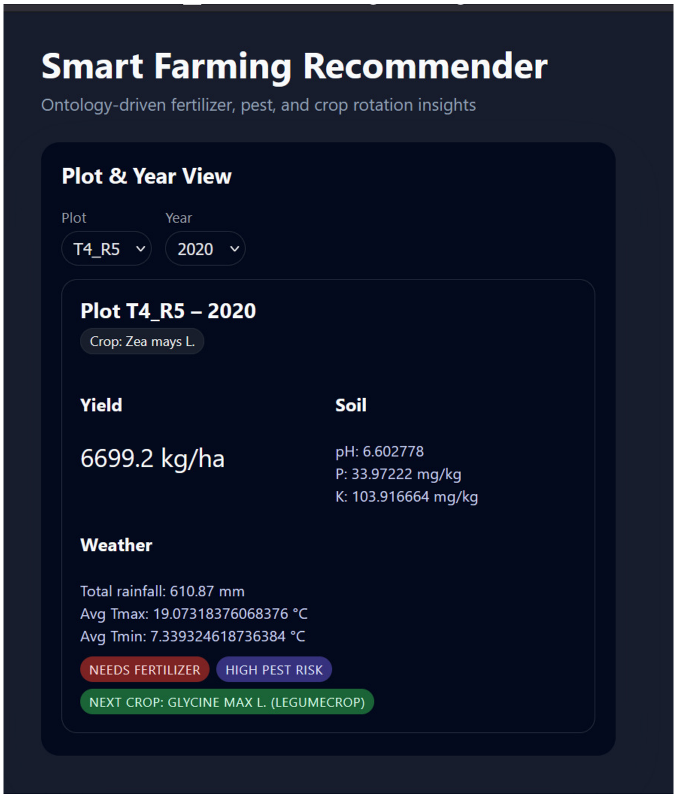

Fig. 3. System output for Plot T4_R5 in 2020 indicating fertilizer requirement and pest-risk level based on soil nutrients and rainfall.

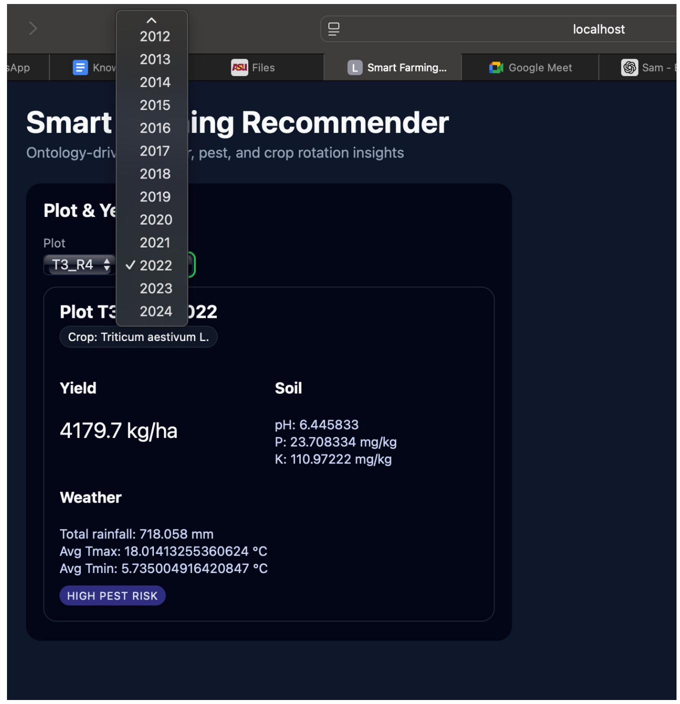

Fig. 4. Dynamic year selection (2012–2024) retrieved from the knowledge graph using SPARQL queries.

records (2012–2024), verifying correct linkage across soil, yield, and weather datasets.

Fig. 5 illustrates the dynamic retrieval of plot–replicate identifiers using SPARQL queries that bind yield, soil, and weather records to their corresponding plots. These results demonstrate accurate and consistent cross-domain integration within the knowledge graph.

C. Usability and Visualization

The interactive dashboard consolidates semantic reasoning results, raw agronomic data, and SWRL-inferred recommendations into a unified visualization. The interface presents yield, soil, and weather summaries together with fertilizer alerts, pest-risk warnings, and next-crop recommendations in an interpretable format. The informal user evaluation indicated that the system improved the understanding of crop-transition logic and fertilizer timing decisions, demonstrating practical benefits for interpretability and decision support in farming contexts.

D. Summary of Findings

Across all tested scenarios, the system achieved:

- 100% SWRL rule execution without conflicts,
- accurate SPARQL retrieval of multi-domain observations,
- seamless integration of crop, soil, and weather data,
- clear visualization of reasoning outputs through the dashboard.

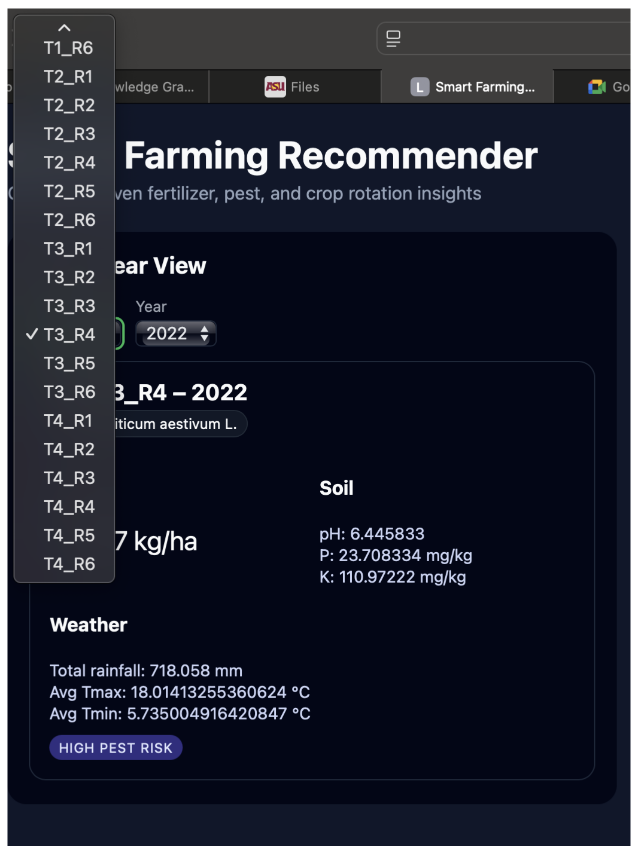

Fig. 5. Plot selector populated using SPARQL-based retrieval of all plot–replicate identifiers.

These results show that combining OWL 2 semantics, SOSA-aligned observations, SWRL reasoning, and SPARQL querying provides a robust foundation for intelligent, knowledge-driven agricultural decision-making.

IX. Conclusion and Future Work

This work presents a unified ontology-driven framework for intelligent farming that integrates soil, weather, yield, and crop data into a semantically rich knowledge graph. By aligning observation records with the SOSA ontology and encoding agronomic logic using SWRL rules, the system is able to infer fertilizer requirements, pest-risk levels, and next-season crop recommendations with high interpretability. SPARQL queries serve as the retrieval layer for combining multi-domain observations and presenting reasoning results through a lightweight, user-friendly dashboard interface.

Evaluation across multiple plots and years demonstrated consistent rule execution, accurate SPARQL-based data integration, and clear visualization of recommendations. These findings highlight the effectiveness of semantic technologies in supporting transparent, evidence-based agricultural decision-making. The system shows that knowledge-graph techniques can play a fundamental role in bridging agronomic data silos and enabling explainable recommendation pipelines.

Future Work:

Several opportunities exist to advance this framework:

- **Expand the ontology:** Incorporate plant disease ontologies, fertilizer taxonomy vocabularies, and soil health indices to broaden the reasoning capabilities.
- **Temporal and geospatial reasoning:** Extend the model by adding time-series relationships, spatial plot boundaries, and crop rotation cycles spanning multiple years.
- **Integration with external data sources:** Automatically ingest real-time weather forecasts, satellite-derived soil moisture data, and sensor streams to improve responsiveness.
- **Advanced reasoning methods:** Combine SWRL rules with probabilistic reasoning or machine-learning models to handle uncertainty and enhance prediction robustness.
- **Farmer-facing decision tools:** Deploy the system as a cloud service with mobile interfaces and multi-user support for large-scale agricultural operations.

Overall, this work demonstrates how semantic technologies, when combined with rule-based reasoning and domain-specific observations, can deliver actionable and interpretable insights for sustainable and intelligent farming practices.

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